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Financing Innovation in Europe*

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- Policy paper: "*Financial Integration, Financing Constraints, and Innovation in Europe: Is more better?*"
- Data report: "*Patent Measures of European Firms: Exploratory Data Analysis, Technical Report, and Related Literature*"
- "*The Impact of Available Financial Lending Resources on Firms' Patented Inventions*"
- "*Deeper Pockets, Better Inventions? Evidence from Financial Market Integration*"

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Financial Integration, Financing Constraints, and Innovation in Europe: Is more better?*

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1 Introduction

A large number of policy initiatives in the European Union and its member states are grounded in the assumption that there is a gap between the demand and supply for financial resources to fund innovations, such as various components of the Capital Market Union. With this policy report, we approach this underlying assumption by addressing two main questions, namely: how are innovations financed and how do changes in the availability of funding affect the type and amount of inventions firms actually introduce to the market? We base our analysis on existing literature as well as own research on the effects of financial integration and the relaxation of financial constraints in the EU on firm inventive activities. We do not only aim to carve out a causal effect of the availability of more financial resources on inventive outcomes, but also try to shed light on the potentially different effects of more financial resources on the quantity as well as the quality of inventions.

We use the circumstance that a number of policy initiatives in Europe have affected the relationship between financing and innovation in the past. This allows us to also compare the European experience with the one in the US where nationwide policy initiatives and shocks affect federal states differently. More particular, these events enable the investigation of the causal effect of changes in financing on corporate innovation in a deeper and more thorough manner in a European context.

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Since its initial years, the European Community has expanded its institutional scope and geographic reach continuously. One of the key issues of the Union has been the integration of financial markets across member states. As such, financial integration has always been a cornerstone of European integration, in particular with the creation of single European market for financial services (Stavárek *et al.* 2011). The process of the European financial integration and the creation of a single (financial) market was mainly motivated by the objective to improve the overall efficiency of the European market and in particular to foster economic dynamics and growth. Thereby, the effect of financial liberalization and integration on economic growth played a key role. We aim to investigate this mechanism in rather granular means by discussing a number of aspects of this process in particular with regard to the effect of the bank-lending channel on innovation. We embed this analysis into a discussion of the effect of financing on inventive output. Rather than focusing on the quantitative impact of (more) financing on (more) innovation, we aim for a discussion with more facets. In particular, we address the impact of changing access to finance on the quality of inventions as measured by different proxies.

We proceed as follows. In the next section, we provide the stage by discussing findings from the (recent) literature on the relation between financing and innovation. In the subsequent two sections, we provide evidence of our analyses utilizing the European Patent Office (EPO) data by looking into the effect of the strengthening of Pan-European financial constraints in the course of an exercise of the European Banking Authority and its consequences of a number of dimensions of firms' patenting activities. In a similar vein, we outline our findings of a staggered financial liberalization procedure on corporate inventions. From all this, we deduce a number of key policy implications in our last session which also provides an outlook for a further research agenda.

2 Financing Innovation

Innovation is a key, if not the key driver of economic growth and dynamics (see e.g. Grossman and Helpman 1993). In contrast to other factors of production, it does not necessarily exhibit diminishing returns, thereby allowing it to remain the determinant of long-run steady-state growth. The main reason why innovative activities in contrast to physical capital accumulation do not run into the trap of diminishing returns is the fact that new knowledge generated by innovation is non-rival. Non-rivalry of innovation output makes it, however, difficult to appropriate its returns. Private returns to innovation typically are below the social ones due to the partial appropriability of social returns. This observation has led policymakers to initiate a set of policy interventions such as the patent system, government support for research and development, tax incentives and a whole set of further measures to overcome this problem (cf. Hall and Lerner 2010).

While the non-appropriability of the returns to innovation applies to an owner-financed innovation project, there is a second set of efficiency problems associated with the financing of innovation which has been debated in economics since the writings of Joseph Schumpeter (see Schumpeter

2010). In a frictionless Miller-Modigliani world, the source of financing would not matter for profitable projects to be realized and implemented. There exist, however, a number of key aspects of innovation going beyond the usual asymmetric information concerns of financing investments, which make appropriate financing of research and development even more cumbersome and the source of financing matter even more. First, it has to be noted that innovations are often closely linked to the human capital of highly skilled personnel, such as natural and computer scientists as well as engineers. Obviously, this human capital is non-alienable in the context of financial contracts. On this basis, it is difficult to allocate property rights and write financial contracts (see Aghion and Tirole 1994). Hence, in contrast to physical asset collateralization of inventions and innovation is clearly more of a challenge. Second, returns to innovation are not only highly uncertain (making it thereby a more risky investment) but also extremely skewed. The degree of this skewness is – given that innovation is often a sequential process in a technological trajectory – very difficult to assess for outside financiers, in particular at the beginning of the technological trajectory (see, e.g. Kerr and Nanda 2015). Finally, the degree of asymmetric information (moral hazard and adverse selection) is often significantly higher than with ordinary investment in physical assets. Taking all these aspects together may not only lead to a potential gap for funding innovation with external financing but also makes the capital structure a relevant factor. Based on recent evidence, we would like to argue in the following that the pecking order of innovation finance is life-cycle dependent.

In the last two decades, there has been significant research on the topic most notably on venture capital (VC) financing of innovation for young, start-up firms. These firms lack in particular private wealth to undertake and finance research and development such that external funds are most needed. Venture capitalists act not only as providers of external capital (equity) but combine this with active involvement and advice, thereby potentially solving a hold-up problem of providing this kind of external funding (see Casamatta 2003). The venture capital industry has developed a series of instruments, which address and mitigate the informational and control problems which are often very pronounced with young start-up firms. Very detailed financial contracting (see Kaplan and Strömberg 2003) comprising control as well as exit rights (cf. Bienz and Walz 2010) are aimed to reduce informational frictions. Together with proper financial instruments such as convertible securities (see Schmidt 2003) financial contracts provide solutions to the two-sided moral hazard problems in the interaction between the innovative entrepreneurs and the VCs. Other measures such as staged financing and milestone financing address hold-up problems throughout the course of the invention and innovation process (Bienz and Hirsch 2011) and allow for temporary investment and exit of the VC from the innovative financing role (see Neus and Walz 2005). Overall, this research clearly shows that the VC industry has developed corporate governance and financial contracting measures, which allow to cope with the aforementioned informational frictions associated with innovative activities leading to significant dynamics in financing young, innovative start-ups around the world. These dynamics, however, differ quite a lot across jurisdictions, with regard to levels as well as to growth rates.

One of the problems associated with the link between venture capital financing of young, innovative start-ups is to investigate the causal relationship between financing an innovation properly. The problem is obvious. A positive correlation can lend itself to various interpretations. First, the causality could go the either way round. Rather than venture capital spurring innovation, it might very well be that more technological opportunity will increase the amount of funds available for venture capital searching for yield in the new technologies. Second, there might exist unobserved factors such as new entrepreneurial and innovative capacity, which jointly may drive venture capital financing as well as innovations. Finally, it might indeed be the case that more venture capital financing is causing more innovation, hence leading potentially to more economic growth and dynamics. Identifying the causal effect at the firm level is very much complicated by the fact that venture capital firms, by definition, pick at least potentially (highly) innovative firms. Given this selection effect, it is clearly a difficult task to identify any causal relationship at the firm level. For this reason, Kortum and Lerner (2001) address the causality of more venture capital financing on innovative behavior at the aggregate industry level. They examine the influence of venture capital on the number of patented innovations in the US for three decades from the early 1970s to the late 1990s. In order to overcome the endogeneity concerns they use an exogenous policy shift which facilitated venture capital fundraising (and hence investment) in the late 1970s. They show using this identification procedures that venture capital increased the rate of innovation nationwide significantly (by almost 8 percent) despite a rather small size of the venture capital industry in the US at that time.

Unfortunately, the exogenous event used in Kortum and Lerner (2001) dates back to the 1970s implying that there this is a lack of more recent evidence on the positive causal effect of venture capital financing in innovation. There are other more indirect ways to link financial development to innovation in cross-country studies (see e.g. Hsu *et al.* 2014) but since such studies are lacking precise evidence on the channel between the financing source and innovative activities we view it as a quite incomplete substitute for precise micro-evidence on the transmission of more financing on innovation.

Innovative firms in later stages of their life-cycle are in a different position relative to young start-up companies when it comes to the financing of innovation. Potentially, they have more internal funds available to finance innovative activities. Further, they could also rely on other tangible assets or former intellectual property as collateral. In contrast to the widespread previous opinion in the literature as well as in the public debate, recent research has shown that the pecking order of financing innovation in these firms can be quite different. A number of papers have shown that bank debt plays a potentially large role to finance innovation in more mature firms[1]. Nanda

[1] There is even some evidence that innovation in young, start-up firms is affected by more access to bank debt (see e.g. Chava *et al.* 2013) and that these firms indeed rely significantly on financing by banks (see Hirsch and

and Nicholas (2014) use historical data from the 1930s to investigate the effect of bank financing of innovation on innovation. By employing micro-data on corporate R&D they are able to examine the link between financial sector distress and technological development. Their panel spans the period 1920 to 1938, so they can examine innovation before, during and after the banking crisis of the Great Depression. Furthermore, they link these data to county-level data on banking in the United States. They exploit cross-county variations in the severity of bank distress faced by the firms in order to understand the extent to which bank distress in a firm's local banking market affected the level and trajectory of corporate innovation. Their findings indicate that bank distress during the Great Depression was associated with a large reduction in the level and quality of innovation by the firms that were most affected.

Using more recent evidence Mann (2018) underscores the importance of the bank-lending channel on corporate innovation in the US. He shows that secured debt is an important source of financing for innovation, and patents are an important form of collateral supporting this financing. His data shows that companies with patent-backed debt perform an amazing 49% of public-sector R&D and 41% of patenting since 2003. On this basis, the effect of an exogenous strengthening in creditor is investigated. It turns out that along with the increase in collateral usage and debt issuance, firms experiencing a strengthening of creditor rights to patent collateral exhibit a 2.67% relative increase in R&D expenditure as a fraction of total assets. This provides clear evidence that a strengthening of the bank credit channel increases research and development effort and hence the likelihood of more innovations. Given the different legal and institutional frameworks it is, however, questionable whether these findings can be easily translated into the European context.

Amore *et al.* (2013) employ the staggered passage of interstate banking deregulation in the U.S. banking industry during the 1980s and 1990s as a source of exogenous variations across different states. They find strong evidence that banking development influences innovation by publicly traded manufacturing firms. By allowing bank holding companies to expand across states, this state-level deregulation increased the credit supply, led to better screening and monitoring technologies, and facilitated banks' geographic diversification of credit risk. After controlling for firm characteristics, firm fixed effects and other potential co-founding factors, it turns out that interstate banking deregulation caused a 12.6% rise in the number of patents granted to firms. Furthermore, they find a more than 10 percent increase in the importance of patents, measured by citations received from future patent applications by other firms.

In contrast, Cornaggia *et al.* (2015) detect robust evidence that banking competition reduces state-level innovation by public corporations headquartered within deregulating states. Innovation, however, increases among private firms that are dependent on external finance and that have limited access to credit from local banks. They interpret their findings as an indication of a crowding out of innovation finance for publicly traded firms by funds flowing to smaller, non-listed firms.

Walz 2018).

Hence, previous research indicates that the bank debt channel matters for corporate innovation, mainly with data from the US. In order to conduct proper policies, it is, however, of utmost importance to analyze this empirical relationship in the context of the relevant political environment. In order to provide well-suited recommendations for European policy makers, thorough analyses regarding the impact of financial resources on firms' inventive activities have to be conducted in a European context. This essay can be viewed as a starting point for that task.

In addition to this, the underlying mechanisms of how finance affects corporate inventions has to be investigated in detail. On the one hand, it is crucial to investigate the extent to which the availability of more financial resources affects the outcome of corporate innovation, i.e. by moving beyond pure input measures such as research and development expenditures. Furthermore, policy makers should get an understanding of whether more financing is always better by addressing the potential quantity-quality trade-off of more innovation financing: does more financing lead not only to more innovation but also higher quality innovation. Finally, moving beyond pure correlational analysis and identifying the causal effect of economic policies in this context is key to inform policy-makers about optimally to be designed policy initiatives.

In order to address all three tasks, we have employed the very granular data of the European Patent Office to investigate a number of aspects, which allow us to deduce proper insights into the above mentioned key issues. In the following sections, we will briefly summarize and discuss these analyses. In the next subsection we outline an analysis of an exogenous shock to the European banking industry and its consequences on the innovation behavior of affected firms (in both quantity as well as quality terms). Thereby, a key issue is the role of financial constraints on the transmission channel. In the second step, by looking into the consequences of a staggered introduction of policies which strengthened financial integration in the European Union it can investigate to what degree these staggered measures causally affected the quantity-quality aspects of corporate inventions.

3 Exogenous Shock in Financial Resources and Innovation

In the following subchapter, the findings of Krzyzanowski (2019) regarding the impact of a negative shock in the availability of firms' financial resources on *budgetary* and *qualitative* dimensions of their patented inventions are presented. For this purpose, the European Capital Exercise, which was conducted by the European Banking Authority in 2011 and required a subset of European banks (*EBA banks*) to reach and maintain a 9 percent core tier 1 capital ratio, is utilized. Building on a unique, self-generated dataset, the results of this analysis support the more finance - more innovation view. Higher bank capital requirements resulting in lower financial resources available for firm lending activities lead to less firm-level innovation activity in terms of budgetary patent measures. Qualitative dimensions of patented firm inventions, on the other hand, are affected positively.

The paper is based on data from numerous sources. Information on firms' financial statements are taken from the Amadeus database which is provided by Bureau van Dijk. Historical information on firm-bank loan contracts are taken from the Dealscan database which were obtained from Wharton Research Data Services.

The EBA capital exercise is well suited for investigating the impact of financial resources on firms' inventing activities due to the following reasons: First, the EBA measures have been criticised for having contributed to a credit crunch in the euro area.[2] Recent empirical findings support this notion. It was shown that EBA banks - i.e. the subset of European banks which had to increase their capital ratios in the course of this capital exercise - raised their regulatory capital ratios mainly by a strong reduction in outstanding syndicated customer loans compared to banks which were not subject to the higher capital requirements (Gropp *et al.*, 2018). Further related literature also shows that banks' capital requirements have a strong impact on their lending capabilities (Gambacorta and Mistrulli, 2004; Altunbas *et al.*, 2010). These requirements are typically linked to the individual bank's amount of outstanding credits. If violations to them are costly, banks aim at minimizing their risk of future capital inadequacy (Van den Heuvel *et al.*, 2002). As a consequence, stronger capital rules may result in immediate adjustments in banks' lending amounts, because capital raises may become very expensive or even unfeasible - particularly in periods of financial distress. Accordingly, stronger capital requirements may limit banks' lending abilities and decrease their credit supply towards potential borrowers (Gambacorta and Marques-Ibanez, 2011). Shocks regarding banks' capital requirements may result in restrictions in the external supply of capital, thereby propagating from the financial to the non-financial sector and having effects on real economic outcomes.

The capital exercise is utilized in Krzyzanowski (2019) in a difference-in-difference estimation setup. Controlling for firm-, industry- and macro-specific variables, the EBA capital exercise constitutes a quasi natural experiment in order to analyze how the associated shock affects different dimensions of firms' patented inventions for those firms which are classified as being exposed to the consequences of the exercise. The exogenous treatment is defined as the introduction of the increased bank capital requirements affecting a subset of European banks. The firms' exposure to the treatment is based on ex ante differences regarding their lending shares to the EBA banks, which will be defined below.

Heterogeneity in the sample is utilized in two distinct ways. First, cross-country variation is introduced by the fact that the EBA banks were chosen based on their national relative market share in terms of their total assets in descending order of their individual share and covering at least 50% of the respective national banking sector as of 2010. As national banking sectors differ with respect to their sizes, the banks included in the EBA capital exercise are somehow

[2]See the statement made by ECB President Mario Draghi on January 12, 2012 in response to questions by journalists : "*I think there are usually, by and large, three reasons why banks may not lend. [...] The second reason is a lack of capital. [...] So your question is about the second, a lack of capital. Now, the EBA exercise was in a sense right in itself, but it was decided at a time when things were very different from what they are today [...]. So in itself under these circumstances the EBA exercise has turned out to be pro-cyclical.* (Draghi, 2012)

disentangled from bank size factors by including banks from different countries with different sizes in the capital exercise. Within-country variation arises from differing degrees of firms' exposure to to the treatment. Firms with a high EBA borrowing share exhibit inter alia 4 percentage points less asset growth and 6 percentage points less investment growth than firms less reliant on funding from EBA banks. In line with these findings and following related literature, the sample of firms in this paper is divided into EBA firms with an above median dependence on credit supply from EBA banks - measured by their EBA borrowing share - and the non-EBA firms with a below median dependence on credit supply from EBA banks (Gropp *et al.*, 2018). The borrowing share of an individual firm j is calculated as follows:

$$\text{EBA Borrowing Share}_\text{j} = \frac{\sum_{\text{i[EBA Banks]}} \sum_{\text{q=2010 Q1}}^{\text{2010 Q4}} \text{Loans}_{\text{ijq}}}{\sum_{\text{i[All Banks]}} \sum_{\text{q=2010 Q1}}^{\text{2010 Q4}} \text{Loans}_{\text{ijq}}}$$

EBA firms are considered as being exposed to the above-described negative impact of the EBA capital exercise on bank lending, whereas the non-EBA firms are considered as being not exposed to the EBA capital exercise. This classification assumes that the EBA capital exercise does not have a uniform effect on the entire sample of firms. Rather, there exists between-firm variation regarding the extend they are considered to be affected by the increased capital requirements during the EBA capital exercise.

The empirical challenge in the context of changes in bank capital requirements is that they usually affect all banks in a given economic area which inhibits cross section variation. Furthermore, if discretionary bank-specific requirements were introduced, these might be correlated with observable bank characteristics and, therefore, be endogenous to banks' balance sheets. However, due to the country-specific bank selection rule of the EBA capital exercise, which covered 50 percent of each national banking sector in descending order of banks' individual market shares, the necessity for increased capital requirements can be disentangled from bank size characteristics on a cross country basis. The underlying rationale is that national banking sectors differ with respect to their size and resulted in a considerable overlap between banks participating and not participating in the capital exercise (Gropp *et al.*, 2018). Therefore, the variation in banks' capital requirements introduced by the EBA capital exercise can be considered to be exogenous. Furthermore, endogeneity should be less of a concern, because empirical estimates in this paper are calculated on firm-level basis, while implementation decisions of the EBA capital exercise are based on a country-bank-level. Finally, the capital exercise can be considered exogenous regarding i) potential preemptive adjustments of banks' balance sheets which would bias downward the effects of the capital exercise on lending, as well as regarding ii) firms' bank choices and lending relations towards certain institutions in advance to the capital exercise due to the unexpected occurrence of the exercise (Mésonnier and Monks, 2015; Gropp *et al.*, 2018).

Both, *qualitative* and *budgetary* dimensions of patented inventions are analyzed in context of the implementation phase of the EBA capital exercise. While previous results find a negative effect of financial constraints on innovative inputs and outputs such as spendings on research and development and patent counts, recent findings analyzing U.S. firms indicate that financial obstacles may benefit *qualitative* outcomes of innovation. For these firms it has been shown that innovative efficiency was improved in the presences of financial constraints (Almeida *et al.*, 2013; Hirshleifer *et al.*, 2013; Cohen *et al.*, 2013). Innovative efficiency was measured in terms of patent citations scaled by R&D expenditures and shown to be value-relevant and increasing future profitability of firms. Building on these findings and for a European context, Krzyzanowski (2019) uses detailed patent measures capturing outcomes classified as capturing qualitative aspects of the underlying patented inventions in order to get a more profound understanding on firms' innovative oucomes in Europe from a budgetary and qualitative perspective.

Qualitative aspects of patented inventions may refer inter alia to those dimensions which contain information regarding to the technological as well as economic value of the underlying invention (Squicciarini *et al.*, 2013). Consequently, a wide array of patent measures can be derived, which mirror different, albeit often interrelated aspects. Furthermore, also *budgetary* dimensions of patented inventions are analyzed. The measures derived capture information regarding the associated costs of a filed patent. They may refer to the total number of patents filed by one firm at different patent offices. According to Article 2 (1) of the European Patent Convention, each European patent applications is associated with filing fees.

The panel structure of the data allows to control not only for unobserved heterogeneity across firms but also for entity-fixed but time varying effects. The following econometric model is established:

$$\begin{aligned} Patent\ Measure_{itc} =& \beta_0 + \beta_1 Exp_{ic} + \beta_2 Post_{t-1} + \beta_3 (Exp_{ic} \cdot Post_{t-1}) \\ & + \beta_4 X_{ic,t-1} + \omega_{c,t-1} + \gamma_{t-1} + u_{ict} \end{aligned}$$

where $Patent\ Measure_{itc}$ refers to different variables referring to *budgetary* or *qualitative* dimensions of patented inventions of firm i in period t from country c. The Exp_{ic} variable is a dummy variable capturing the above-described exposure of firm i from country c to the treatment, i.e. the EBA capital exercise. This variable is set to 1 if the firm belongs to the treatment group in either period in time based on the ex ante classification referring to the firm's EBA lending share. The $Post_{t-1}$ variable is a dummy variable set to 1 if the observation is from the post treatment period in either group. It is assumed, that the patent measures are affected with a one period lag by the treatment. This assumption is based on the consideration that it takes time for inventive outcomes to react to negative shocks in the availability of financial resources. Further firm-specific controls ($X_{ic,t-1}$), macro controls ($\omega_{c,t-1}$), and time controls (γ_{t-1}) are also included.

Based on this empirical setup, the results of this paper support the view that less finance leads to significantly less innovative activities in terms of *budgetary* dimensions. Therefore, the conventional view that a negative shock in the availability of financial resources negatively affects *budgetary* dimensions of inventing outcomes can be supported with the budgetary patent measures utilized in this paper. Additionally, a negative shock in the availability of financial resources has a significantly positive impact on *qualitative* dimensions of patented inventions. These results are backed by numerous robustness tests, for instance by deploying different lead and lag structures in the above-described empirical setup. Therefore, the twofold considerations regarding the two investigated dimensions of outcome variables related to patented inventions provide interesting insights and new perspectives on the effect of the availability of financial resources on firms' inventing activities in Europe.

4 Financial integration and innovation

The previous subchapters describe two key determinants for inventive activities on a firm-level: financial input as well as firms' general business environment. In this subchapter, the two aspects are combined in order to study the effect of alleviating financing constraints on inventive activities on a firm-level (Heller 2019). Against the background of previous findings, two aspects are central in this study. First, financial integration is able to remove financing constraints, which in turn has other real economic effects. Second, finance has heterogeneous effects on the amount and types of inventions that firms introduce to the market.

Access to finance is found to be a key input factor for firms' innovative activities across the entire distribution of firm types (Coad *et al.* 2016). Thus, unlike other characteristics, access to finance does not only affect certain subgroups of firms but is relevant - to varying degree - for all firms. The habitual understanding is that better access to funding and larger amounts of financial resources enhance inventive activities on a firm level: they induce higher spending on R&D (Brown *et al.* 2009, Hall and Lerner 2010), strengthen long-term research investments (Aghion *et al.* 2010), and increase patent filings (Chava *et al.* 2013, Cornaggia *et al.* 2015).

However, alleviating financing constraints may have more diverse effects than just a mere, quantitative increase in investment. In line with the assumption of decreasing returns to investment, i.e. R&D expenses (Lokshin *et al.* 2008), increased funding could be associated with lower average quality of inventive output. Financial constraints can thus incentivize firms to use available resources more cautiously. In fact, several studies show that input resource constraints lead to more efficient use of the existing set of deployable resources (Goldenberg *et al.* 2001, Moreau and Dahl 2005, Gibbert and Scranton 2009). Hence, the removal of financing constraints which served originally as disciplining device may lead to more wasteful investments (Aghion *et al.* 2013). As a result firms may realize also rather incremental, i.e. more marginal, inventions.

Following this line of thought, recent empirical studies provide supportive evidence that the cost and availability of finance affect not only the amount but instead also the type of inventions a firm introduces to the market (Kerr *et al.* 2014, Raiteri 2018). For example, de Rassenfosse and Jaffe (2018) show how changes in the filing costs affect the quality of patents. In their study, the authors find that increases in patenting fees are responsible for crowding out low-quality patents. Particularly firms with large patent portfolios respond to changes in the fee structure by reducing applications for low-quality patents disproportionally. Additionally, first evidence exists on the way the availability of funding affects inventions. The theoretical model by Nanda and Rhodes-Kropf (2016) suggests that financial markets actively drive inventive behavior. The authors illustrate that high-impact inventions require hot financial markets to enable their initial financing, commercialization and diffusion.

Moreover, economic development (King and Levine 1993, la Porta *et al.* 1998, Levine 2005), specifically financial integration (Kerr and Nanda 2009) are considered pivotal for inventive activities, too. Empirical literature has investigated the impact of bank regulation from a de jure perspective on credit availability and credit quality. Bank deregulation is thereby associated with an increased sensitivity of bank-lending decisions to firm performance (Stiroh and Strahan 2003, Bertrand *et al.* 2007). Further, integration potentially helps to reduce entry barriers, improve access to finance (Cetorelli and Strahan 2006), and lower interest rate spreads particularly for small firms (Guiso *et al.* 2006).

Heller (2019) combines the two aspects, access to finance and financial market integration, to study the impact of changes in firms' level of bank finance on inventive output, i.e. the quantity and quality of patents filed. The intuition behind this analysis is that financial harmonization marks a positive shift in the lending conditions of firms domiciled in affected countries, which directly translate to changes in innovation relevant investments by firms. Moreover, theoretical and empirical considerations give rise to the assumption that a positive exogenous shock in financial resources may not only entail positive effects on firms' inventive activities, per se. Both, decreasing returns to investment and the incentivizing effect of resource constraints, are suggestive mechanisms on why the removal of financing constraints induces firms to introduce inventive output of relatively lower average technological quality and, hence, market value.

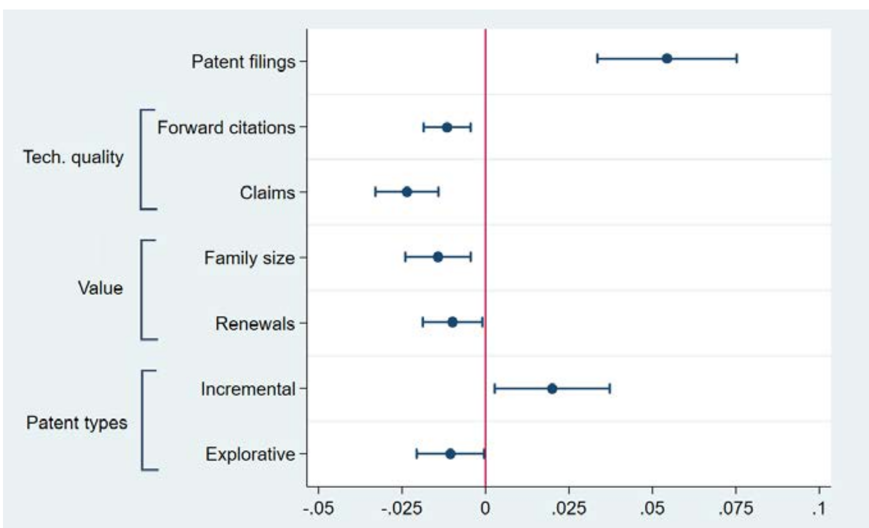
To study these effects, Heller (2019) analyses the so-called Financial Services Action Plan (FSAP), which constitutes one prominent example of financial market integration in the recent past. In 1999, the European Commission officially issued the FSAP, of which the predominant strategic intention was to integrate financial markets within the European Union by further harmonizing its regulatory framework. The EC aimed at developing the legislative framework along four objectives: a single EU wholesale market, open and secure retail banking and insurance markets, state-of-the-art prudential rules and supervision as well as advancing towards an optimal single financial market. Therefore, it asked EU-15 member states to implement 42 legislative amendments over a timespan of six years. These amendments included 29 major pieces of legislation (27 EU Directives and 2

EU Regulations) in the fields of banking, capital markets, corporate law, payment systems, and corporate governance.

The main findings regarding the impact of financial integration on lending complements previous evidence that ascertains a positive impact of the FSAP on financing conditions.[3] More specifically, evidence suggests a stimulating effect of the FSAP on financial market harmonization (Kalemli-Özcan *et al.* 2013) and capital market access (Meier 2018). Complementing this, the analysis shows that the process of financial integration elevated bank lending on a firm level causally. The average firm affected by FSAP amendments increases their bank loan ratio by 26 percent comparing pre- and post-integration levels.

In the final part of the analysis we investigate whether and how these changes in lending translate to firms' patenting activities. To draw causal inferences, heterogeneous effects arising from variation in the responsiveness to financial integration across time and within countries are exploited. Comparing estimates for affected and non-affected firms suggests that increased use of funding does not only translate to increased patenting activities in quantitative terms, but also alters the types of patents filed.

Figure 1: Coefficient plot: Financial integration along patenting dimensions



Notes: This graph plots coefficients of the interaction of the financial integration measure with a dummy equal to one if firm is classified as ex ante financially constrained or zero otherwise capturing the causal effect of relaxed financing constraints on respective patenting dimensions. The dependent variables are patent applications (row I), technological quality (rows II-III) and value-related (rows IV-V) dimensions, and different patent types (rows VI-VII). Regressions include firm-specific controls, firm and country-year fixed effects but estimates are omitted. Standard errors are heteroscedasticity-consistent and clustered at the firm level. Whiskers represent the 90 percent confidence intervals of the estimates.

[3] In a general argumentation, Malcolm *et al.* (2009) stress the importance of the FSAP for providing confidence in the reliability of financial regulation itself. Similarly, Quaglia (2010) argues that the FSAP represented a change in EU strategy away from market opening measures and towards common regulatory measures.

The results from Table 1 suggest that firms, which experience a positive exogenous shift in their access to funding, tend to file more patents but of lower average quality and value. More specifically, the positive shift in the use of bank funding is negatively related to the technological quality of patents. Estimates show that purely value-related measures only decrease marginally. Moreover, respective firms tend to devise fewer explorative inventions but instead adjust their patenting strategy towards rather incremental inventions. Deploying different lag structures indicates that the aforementioned effects become more sizeable over time, which suggests that the adoption process in the availability of funding takes time to translate to inventive activities.

Overall, the results illustrate that the impact of finance on inventive activities is more multilayered than previously suggested. Changes in the level of funding affect not only the magnitude of patents but also value-relevant characteristics of patents filed. Despite a positive effect in quantitative terms, additional funding appears to be detrimental at the margin along several qualitative dimensions of the inventive output. These results do not suggest that financial resources are not important in the innovation process. In contrast, we provide further evidence that appropriate financing is a prerequisite for respective activities. However, our findings emphasize that the marginal benefit of increased funding is not necessarily positive, once a more differentiated view is taken.

5 Conclusion - Summary and Policy Recommendations

The analyses conducted contribute to the literature on the drivers of corporate innovation. In contrast to most existing studies, we focus on firms domiciled in Europe. For this purpose, different European policy initiatives are utilized to analyze the effects of firms access to finance on their patenting activities. To provide a comprehensive picture, two complementing initiatives are considered in a European context: i) policies which entailed a negative impact on firms access to external sources of finance (EBA capital exercise) as well as ii) those helping to mitigate financing constraints (FSAP).

The findings indicate that more finance does not enhance innovative activity per se and less finance is not harmful for firms outcomes of their innovative activities by itself. Based on the idea of more efficient use of available resources, the marginal effect of financial obstacles may even be positive, regarding qualitative dimensions of firms patenting activities. Similarly, we show that additional funding may induce firms to also file patents of releatively lower quality and value.

Based on our findings, several policy recommendations can be derived. From a *governmental* perspective, a main policy implication is that the provision of additional funding to firms should be cautiously considered. Exclusively targeting the level of available funding is not an efficient strategy to improve innovation processes and inventing activities in a comprehensive manner. It appears more appropriate to create innovation-friendly environments which include sufficient but not excessive funding as well as reliable safety grids but no arbitrary guarantees. Hence, policy initiatives should focus on well-balanced schemes such that additional funding is efficiently deployed.

In fact, numerous existing European and national political initiatives already aim at supporting firms' engagements in innovative activities. For instance, they provide established medium-sized firms with favorable lending conditions through the "ERP-Innovationsprogramm" (see BMWi 2016; KfW 2016) or broaden the access of SMEs to market-based sources of financing at each stage of their development through the SME Growth Market framework (see European Commission 2018a, MiFID II). Furthermore, the European Commission has launched a Pan-European "Venture Capital Funds-of-Funds programme" (VentureEU) with the aim to boost investment in innovative start-up and scale-up companies across Europe together with the European Investment Fund (European Commission, 2018b). The associated conditions that have to be met by the respective firms in order to obtain access to these resources vary between the different initiatives. The core of these initiatives is, however, to provide European firms with better access to equity and debt financ, per se. For instance, it is stated in MiFID II that *"[I]t is desirable to facilitate access to capital for smaller and medium-sized enterprises [...]. Attention should be focused on how future regulation should further foster and promote the use of that market so as to make it attractive for investors, and provide a lessening of administrative burdens and further incentives for SMEs to access capital markets through SME growth markets"* (European Union, 2014).

Our research clearly indicates that this is too little. More structure of government programs is needed to assure that government initiatives do not lead only to more finance available for research and development. Our results stress that finance as a key input factor for firms' inventive activities has multi-layered implications for their inventing activities, respectively the associated outcomes. We show that in addition to quantitative aspects, qualitative dimensions are particularly affected, too. Thus, we suggest that governmental initiatives which aim at improving firms' access to financial resources should explicitly consider determinants with potential influence on qualitative dimensions of firms' inventing activities. Favorable access to financial resources should be granted condititional on binding objectives which ensure the efficient use of deployable resources. This can help crowding out marginal inventions of low quality and market value.

Complementing these implications, the findings can also be applied to a managerial perspective. Consequently, our results also contain valuable implications from a *corporate* perspective. It can be argued that the findings regarding the qualitative dimensions of patented inventions are partly driven by agency considerations. Managers have incentives to expand their firms beyond optimal size, because this expansion increases their power resulting in higher compensation as well as reputation. Thus, excess financial resources might enduce firms to invest in less valuable projects. Following these considerations, firms should implement mechanisms that circumvent these inefficiencies. One potential way can be the introduction of incentive schemes targeting quantitative as well as qualitative dimensions of firms' measurable inventive activities.

Building on these findings as well as the established implications from governmental and corporate perspectives, the presented results provide the starting point for future research in the fields of corporate finance and the economics of innovation in a European context. Finally, these findings are potentially also fruitful for other related fields of science, such as psychology, behavioral economics, corporate governance and political science.

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Patent Measures of European Firms Exploratory Data Analysis, Technical Report and Related Literature*

Jan Krzyzanowski†

Abstract

This paper provides detailed insights and analyses on multiple self-generated patent measures from a European firm-level perspective. Recent literature acknowledges that it is challenging to navigate in the wealth of data offered by Patstat which are provided by the European Patent Office. In order to obtain a well-profounded understanding of these data, the paper contains structural insights on the Patstat database based on which insightful patent measures which build upon findings and considerations from previous literature are generated. By taking a European firm-level perspective, the paper contributes to the literature on corporate innovative activities. Consequently, the descriptive tables, figures and analyses included in this paper refer for the subset of those Patstat data which are matched to European firm-level data from the Amadeus database. This merged firm-patent-level dataset allows for conducting comparative analyses for each patent measure from multiple firm-level perspectives. In particular, the paper contains detailed descriptive time series analyses and statistical tests which compare the inventive outcomes of small, medium and large firms from different European countries. Further analyses for patent applications filed in different technological sectors are also included. Finally, the paper contains guidance for researchers by providing in-depth overviews on the structure of Patstat as well as descriptions of associated SQL codes which are utilized in order to generate the respective patent measures from the wealth of available data. Thereby, the compilation of patent measures for future research is facilitated.

Keywords: patented inventions, patent measures, exploratory data analysis, Patstat
JEL Classification: C80, C81, D22, O32, O52, Y1

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1 Introduction

The association between patents and inventions is widely accepted in the literature (Bertoni and Tykvová 2015). According to Swann (2009), inventions are the culmination of research activity which contain ideas, sketches or models of new products or processes that may often be patented. Going beyond inventions, innovations refer to those (patented) inventions which are indeed commercially exploited (Bertoni and Tykvová 2015). Patented inventions may be considered as one source of potential innovations. The information included in patent documentations inter alia contain insights on the commercial use of the patented invention which have been used as proxies for innovation in empirical research (Hall et al. 2005). Patents are referred as important indicators for innovation in order to assess the technological competitiveness of innovation systems as they constitute one possible output of R&D processes (Frietsch et al. 2010) and thereby may be considered as an intermediate step between R&D and innovation (OECD 2009). Therefore, it is of great interest for empirical research in the field of economics of innovation to obtain valuable information derived from patenting activities. It is of key importance to understand the wealth of available patent data in order to generate insightful patent measures which build upon the findings from previous literature.

Building on these considerations, the main aim of this paper lies in providing insights into the mutifold information contained in patents from a European firm-level perspective. The analyses conducted in this paper, therefore, refer to the subset of those patent applications from the European Patent Office (EPO) Worldwide Patent Statistical database, Patstat, which are matched to the European firm-financial data from Bureau van Dijk's Amadeus database by utilizing the results of the matching algorithm from Peruzzi et al. (2014). While Patstat constitutes the most prominent database which is designed to assist in statistical research based on patent information, Amadeus contains financial information on public and private companies across Europe which includes standardized consolidated and unconsolidated annual accounts data on company financials from balance sheets and profit-loss statements.
Recent empirical analyses utilize the combined information from Patstat and Amadeus in order to analyze their patenting activities from a European perspective.[1] In depth analyses of deduced patent measures have, however, not been conducted for this subset of European firms so far. While Patstat contains the names of the patent filing natural or legal persons (section 2.3.9 of the 2017 EPO Biblio and Legal Catalog), it does not include information on the applicant being a firm or not. Consequently, Patstat does not enable to filter the database with respect to the nature of the applicant a priori (Peruzzi et al. 2014). By contrast, the devised Patstat-Amadeus dataset utilized in this paper allows to analyze patent data from an European corporate perspective (see figure below). This merged dataset enables to conduct extensive descriptive analyses by comparing firms' patent measure outcomes across different firm size categories as well as across the firm country classifications and the technology sectors of firms' patent applications. Besides this, statistical tests on differences in means, correlation analyses across different

[1]For instance, this linkage is utilized in the research project *"Financing Innovation in Europe"* which was funded by the EPO Academic Research Programme 2017. The paper at hand constitutes one element of this cumulative research project. The financial support received from the EPO as well from the Research Center for Sustainable Architecture for Finance in Europe (SAFE) is gratefully acknowledged.

firm- and invention-dimensions as well as extensive economic intuition regarding the obtained descriptive outcomes are provided and underpinned by relevant related literature. Sophisticated follow-up analyses are conducted between these firm- and invention-specific dimensions, which provide thorough insights to numerous dimensions of firms' inventive activities across European firms between 1995 until 2015. Investigating the properties of different patent-based inventive dimensions for this subset of European firms contributes to the literature on European corporate innovation and contains valuable insights for researchers in the fields of innovation economics, corporate innovation and corporate finance.

Overview - Data Merge and Sample Dataset

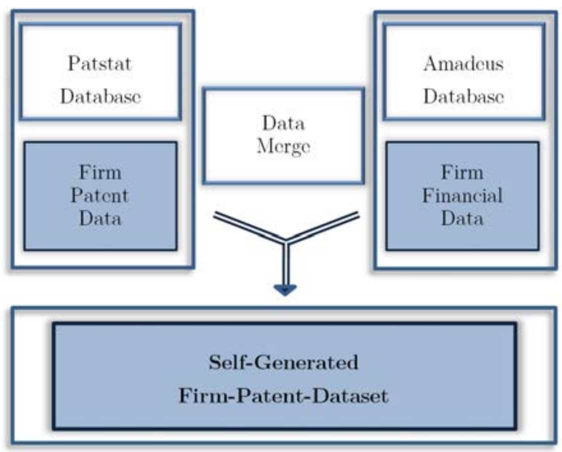


Figure 0.1

The self-generated and analyzed patent measures discussed in this paper relate to different stages of patents' lifes and therefore contain multifold information regarding different dimensions of patented inventions. Some of the measures are insightful with respect to the technological aspects, while other measures are informative regarding the procedural, legal and related value aspects of the underlying inventions. For each of these patent measures, the paper at at hand provides an in depth documentation on the generating process in order to facilitate the empirical work with Patstat. As described in recent literature, it is difficult to navigate in the wealth of data which are offered by Patstat. This results in many prospective users being deterred by its complexity (de Rassenfosse et al. 2014). As the demand for patent data and statistics substantially increased over the last decades (EPO 2017a, de Rassenfosse et al. 2014), it is important to demystify Patstat and the challenging process of generating patent measures from the rich set of available data in Patstat. Therefore, the paper includes a detailed overview on its structure, the datasets included and the way these datasets are linked in the database. Following these insights, additional documentation on the generating process of the self-generated patent measures which is based on Structured Query Language (SQL) is provided. The respective SQL commands are included in the appendix of this paper such that researchers can apply and modify these codes for purposes of their research. The description of the generating process of each patent measure accounts for the fact that the measures i) may be based on information from different Patstat datasets ii) refer to an individual patent vs. refer to the relation of patents towards each other and iii) require appropriately adapted approaches in order to account for the particular structure of Patstat in context of each measure.

The presented descriptive findings, the contained codes and illustrations regarding the generating processes of the patent measures, as well as the background relating to selected findings from previous literature in the fields of economics of patenting and corporate innovation contribute to reduce the perceived complexity of the rich universe of patent data, thereby facilitating and enabling to apply, adjust and refine the fruits from this paper for future patent-related as well as corporate innovation research. Based on these considerations, the remainder of this paper is structured as follows: Section 2 gives an overview on the Patstat database, in particular Patstat Biblio and Patstat Legal Status as well as on the utilized Patstat-Amadeus dataset in order to conduct the descriptive analyses. Furthermore, it gives an overview on the patent measures presented in this paper. Section 3, based on this i) introduces the patent measures derived from Patstat Biblio and discusses the corresponding relevant related literature for each measure, ii) provides details on the Patstat datasets which are used in order to generate each measure and iii) contains the descriptive analyses in the respective subsections for each patent measure. Section 4 performs analogous analyses for the patent measures derived from Patstat Legal Status. Section 5 concludes. In section 6, the first part of the appendix comprises numerous additional descriptives for the patent measures discussed in this paper, while in section 7 details regarding the generating process of the patent measures are contained, including the respective commands as well as further explanations on the utilized data from Patstat.

2 Patstat Database and Descriptive Firm-Level Dataset

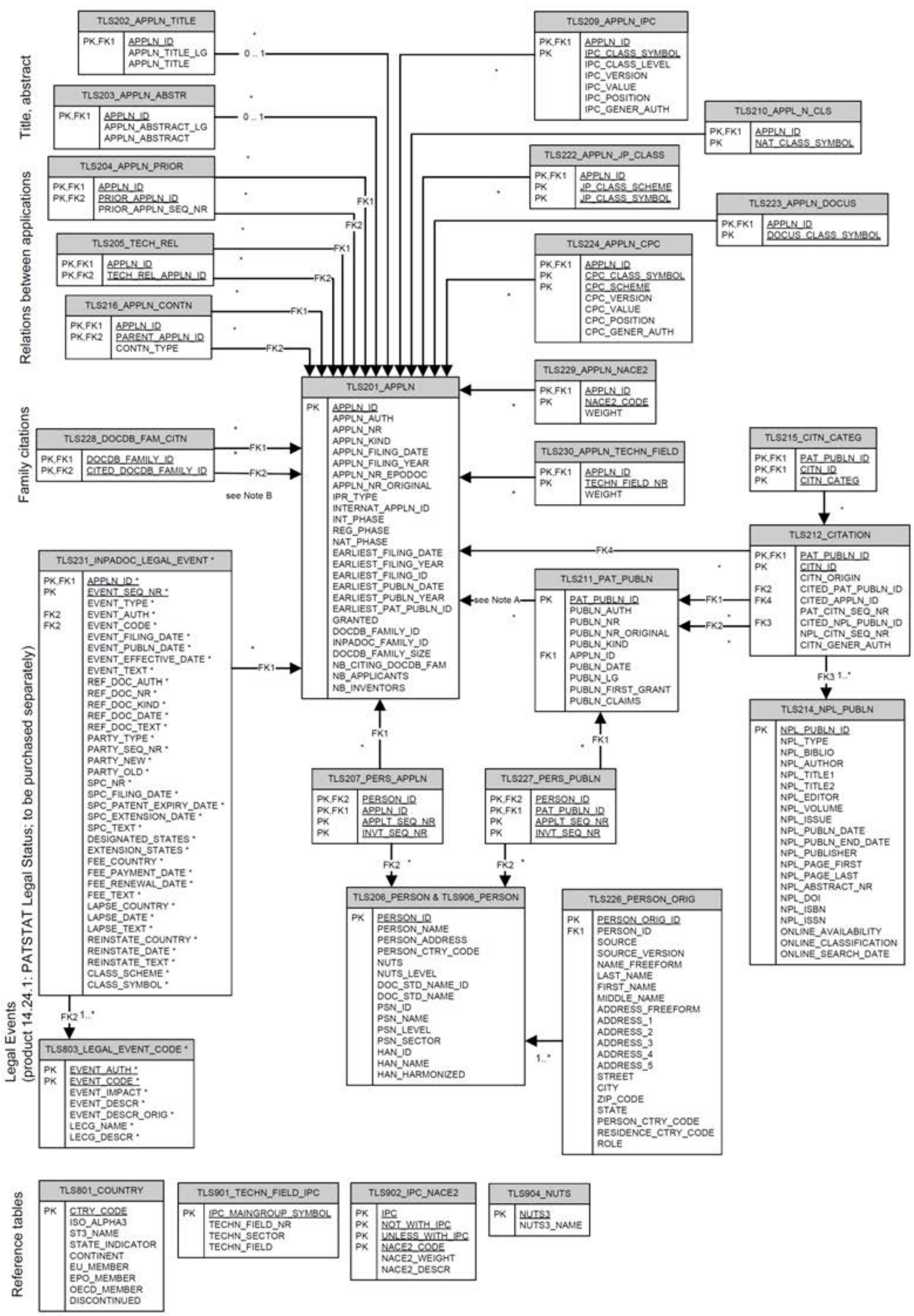
The EPO Worldwide Patent Statistics Database, Patstat, gathers standardized data for almost all of the world's patent offices (OECD 2009). It consists of different individual products, while *Patstat Biblio* and *Patstat Legal Status* constitute the major part of the Patstat universe (EPO 2017a,b). This section provides an overview on these two databases, based on which the patent measures are generated and discussed for the merged set of European firms from the Amadeus database in the subsequent sections. Additionally, descriptives on the included European firms from the Amadeus database are contained in this section.

2.1 Patstat Biblio and Patstat Legal Status

Patstat Biblio has a worldwide coverage and contains raw bibliographic information about applications and publications which include the names of applicants, technology classes, procedural information, the legal status of patents, i.e. whether a patent was granted or not as well as information on citations of patents. Those information are obtained for over 100 million patent records and 90 patent issuing authorities. The paper at hand analyzes the patenting activities of those European firms which could be linked to firm financial data from Amadeus and which file their patent applications at different application authorities worldwide. Notably, the information from Patstat are available regardless of the patent office at which the application is filed because the information requirements and procedures are quite standardized throughout the world (OECD 2009).

Complementing these data, *Patstat Legal Status* contains in depth information about the legal events that occurred during the life of a patent before or after grant. Those events include the payment of renewal fees, withdrawals and patent oppositions (EPO 2017a). Notably, some of the procedural information are not available from the patents themselves, but are documented by the respective patent offices (OECD 2009). Patstat Biblio and Legal Status constitute a multi-layered database which consists of multiple datasets, each containing information on specific patent related topics. All of them refer directly or indirectly to the dataset TLS201_Appln, as can be seen from the figure below.

Figure 0.2: Patstat Biblio and Patstat Legal Status Overview



Source: EPO Biblio and Legal Status Data Catalog (2017)

According to Chapter 5.1 of the 2017 EPO Biblio and Legal Data Catalog, TLS201_Appln contains the key bibliographical data relevant to identify a patent application. This table is of essential importance from a database structure point of view because it is the linking element to other datasets of the database. Therefore, TLS201_Appln can be considered as the core dataset of the Patstat Biblio and Patstat Legal Status database. The primary key of the TLS201_Appln dataset is the application identifier (*appln_ id*). Relating to Chapter 6.9 of the EPO Biblio and Legal Data Catalog, this is a technical unique identifier for a combination of application authority, application number and application kind which remains the same across different Patstat editions. As can be seen from the above figure, this identifier is used to merge the information from numerous other datasets from the Patstat universe with each other.[2] Information from multiple different datasets are utilized in order to generate the patent measures presented in this paper. Specifics regarding these datasets and their relevance for the generating process of each patent measure are described in the following relevant subsections of this paper and in more detail in the corresponding sections of the appendix.

2.2 Descriptive Dataset

As outlined above, the descriptive analyses of the patent measures which are derived from Patstat are conducted for the subset of those inventive European firms which contain information on both, patent data from Patstat as well as firm-level financial data from Amadeus. For this purpose, the matching algorithm provided by Peruzzi et al. (2014) is utilized, as Patstat and Amadeus do not share a common, unique identifier which would enable a direct link of the contained information from the two databases. Based on the resulting matching table which links the firm identifier from Amadeus (*bvd_ id*) with person ids from Patstat (*person_ id*), it is possible to match the firm-level financial data which are contained in Amadeus with the wealth of patent data from Patstat.

According to the elaborations and assessments from Peruzzi et al. (2014), around 40 percent of the patents contained in Patstat could be linked to a company from Amadeus. On the other hand, the percentage of companies for which a Patstat entry was found is substantially lower and varies across countries between around 0.5 percent of the French firms to around 3 percent of the German firms contained in Amadeus. The authors explain these twofold descriptive findings by the fact that company databases like Amadeus include all kinds of companies going beyond those which are involved with patenting activities. Besides this, differences in economic and business structures contribute to explain the established differences. Therefore, sectors like manufacturing and scientific activities were shown to have larger shares of firms matched to Patstat.

Building on these considerations and utilizing the information from Amadeus, the following descriptives provide an overview on the firms included in the analysis of this paper. For this purpose, selected firm financial characteristics as well as firm industry characteristics are depicted in the subsequent tables which also contain comparative analyses over the considered time frame between 1995 to 2015. In this vein, the first table below provides an overview on some firm financials of the analyzed firms which are classified into

[2] The underlined variables from the above figure refer to the primary key which used for merging purposes.

different size categories within four distinct time windows (1995-1999; 2000-2004; 2005-2009; 2010-2015). Based on the classification scheme provided by the European Commission, firms are categorized as i) *small* if they have less than 50 employees and a turnover below 10 mEur, ii) *medium* if they have between 50 and 250 employees and a turnover between 10 - 50 mEur and iii) *large* if they have 250 or more employees and a turnover above 50 mEur.[3] The descriptive analyses below refer to the firm financial characteristics of those firms from Amadeus which also contained patent information from Patstat.

Amadeus-Patstat Firm Sample – Descriptives Part 1
[Means over Firm Size Classifications]

		Firm Size Classifications		
Firm Financials	Time Frames	Small Firms	Medium Firms	Large Firms
Cash Ratio	1995 – 1999	0,17	0,10	0,09
	2000 – 2004	0,19	0,10	0,11
	2005 – 2009	0,20	0,10	0,14
	2010 – 2015	0,19	0,12	0,12
Debt Ratio	1995 – 1999	0,65	0,63	0,63
	2000 – 2004	0,64	0,62	0,66
	2005 – 2009	0,66	0,63	0,67
	2010 – 2015	0,59	0,57	0,58
EBITDA/Assets Ratio	1995 – 1999	0,65	0,63	0,63
	2000 – 2004	0,64	0,62	0,66
	2005 – 2009	0,66	0,63	0,67
	2010 – 2015	0,59	0,57	0,58
Total Assets (mn)	1995 – 1999	9,2	20,8	345,8
	2000 – 2004	8,5	25,2	287,1
	2005 – 2009	8,5	28,0	177,4
	2010 – 2015	15,7	32,7	314,0
Turnover (mn)	1995 – 1999	2,3	19,4	285,6
	2000 – 2004	2,3	22,4	286,8
	2005 – 2009	2,7	26,6	295,8
	2010 – 2015	5,8	32,3	301,0
Number of Employees (Mean)		16	129	1050
Number of Firms (Mean)		3194	1854	6631

Table 0.1

As can be seen from the table above, the firm financial descriptives of the mean outcomes are depicted in the first two columns for each time frame, while the respective mean outcomes for the small, medium and large firms are provided in the adjacent columns. It can be seen that the cash ratio means as well as the debt ratio and the EBITDA to assets ratio means evolve relatively stable within each firm size category over time, while in the most current time frame a drop within the debt ratio and the EBITDA to assets ratios can be observed across all firm sizes. Furthermore, the cash ratios of the small firms involved with patenting activities lie systematically above the cash ratios of the medium and large firms in all time windows considered. Not surprisingly and apart from these relative measures, the total assets as well as the firms' turnover vary considerably across the firm sizes. Besides this, some variation in the evolvement of the total assets and the turnover can be observed within each firm size category over time. While these variations are to a certain extent driven by firm-specific or business-cycle related factors, they may also be partly attributable to the fact that the above descriptives on the firm financials are in each time frame limited to the set of those patenting firms for which inventive outcomes are available.[4] Over the whole

[3]See Recommendation of EU-Commission (2003) notified under the document number C(2003) 1422.
[4]Therefore, it is possible that a firm was not involved with inventive activities in the first time frame, but became

time frame considered, it can be seen that on average around 6600 large, 1900 medium and 3200 small firms are included in the Amadeus-Patstat dataset with on average 1050, 129 and 16 employees. Building on this, the second set of descriptives below provides further analyses by considering comparisons across firm countries and firm industries.

Amadeus-Patstat Firm Sample – Descriptives Part 2
[Means over Firm Countries and Industries]

Firm Characteristics		Firm Countries							
		AT	BE	DE	FI	FR	GB	NL	SE
Number of Firms	Small Firms	57	153	126	417	1331	410	37	626
	Medium Firms	49	72	472	102	519	470	64	92
	Large Firms	211	165	2664	136	656	2033	533	228
Total Assets (mn)	Small Firms	7,5	14,5	7,7	2,5	8,6	9,3	9,4	8,8
	Medium Firms	27,2	25,9	28,3	26,8	24,9	23,3	23,4	43,8
	Large Firms	207,9	368,2	280,5	401,3	346,8	209,0	186,3	368,8
Firm Industry Shares	Agriculture & Mining	0,01	0,03	0,00	0,02	0,01	0,02	0,02	0,02
	Manufacturing	0,47	0,41	0,49	0,45	0,47	0,39	0,27	0,36
	Electricity	0,01	0,02	0,01	0,01	0,01	0,01	0,01	0,01
	Construction	0,04	0,06	0,04	0,08	0,05	0,04	0,04	0,03
	Retail Trade	0,15	0,17	0,16	0,11	0,13	0,08	0,17	0,14
	Transportation	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01
	Info & Communication	0,03	0,05	0,03	0,09	0,06	0,08	0,03	0,07
	Finance & Insurance	0,02	0,03	0,01	0,01	0,03	0,02	0,20	0,02
	Real Estate	0,01	0,02	0,01	0,02	0,01	0,00	0,01	0,01
	Scientific Activities	0,16	0,15	0,19	0,16	0,17	0,15	0,17	0,28
	Administration	0,05	0,02	0,03	0,01	0,02	0,09	0,03	0,01
	Other	0,04	0,03	0,02	0,03	0,03	0,11	0,04	0,04

Table 0.2

From the table above, it can be deduced how the average numbers of firms are assigned in the three firm size classifications to the different countries. Not surprisingly, the largest shares of firms stem from the large economies Germany, France and Great Britain, while it is interesting to note that particularly in France substantially more small firms were merged between Patstat and Amadeus relative to the other large economies. By analogy, relatively many small-sized firms are contained in Belgium, Finland and Sweden, while in Austria, Germany, Great Britain and the Netherlands most of the firms included are either large or medium-sized. These descriptive outcomes are attributable to the matching algorithm results provided by Peruzzi et al. (2014). In terms of total assets, it is interesting to note that the average size of small and medium-sized firms is quite comparable across the countries considered, while the average size between large firms shows greater variation between the different countries. Finally, in terms of firm industries, it can be seen that firms from the manufacturing sector have the largest shares across all countries considered, followed by the retail as well as the scientific services sector. These results are in line with the findings from Peruzzi et al. (2014), according to which the highest percentages of companies matched to Patstat come from the manufacturing sector, followed by the mining, management and the scientific services sector.

Building on this merged dataset, the person ids from Patstat, which are contained in the utilized matching table between Patstat and Amadeus, constitute the starting point in order to generate the patent measures

active in patenting in the second time frame (and vice versa). In any case, the above table refers in each time frame solely to the set of those firms for which inventive activities from Patstat were linked to the respective information from Amadeus based on the firm identifier from Amadeus (bvd_id) and the person id from Patstat ($person\_id$).

based on the information contained in Patstat for the above described subset of European firms.[5] In order to generate the patent measures, the person ids need to be linked within Patstat to the associated application ids from Patstat in a first step. The TLS207_Pers_Appln table (see Figure 1 above) contains the link between the person id and the appln id. Notably, one person id may contain numerous application identifiers, as multiple applications can be filed by single entities. Therefore, subsection 7.1 in the appendix of this paper contains the command which links the European firms' person ids from the above-described matching outcomes with their corresponding application ids. In subsequent steps, the resulting set of unique application ids is imported into an indicator table which is updated with patent measures generated by the respective commands presented in the relevant subsections of the appendix.[6]

2.3 Patent Measures - Overview

Following these considerations, this subsection provides an overview on the patent measures which are generated and discussed for the above-described set of European firms in the remainder of this paper. Patent-based measures have several uses as they allow for measuring the inventiveness of countries, regions, firms and technological sectors (OECD 2009). The figure below depicts the patent application and grant procedure which includes an overview on the derived patent measures that are generated and analyzed in the remainder of this paper.

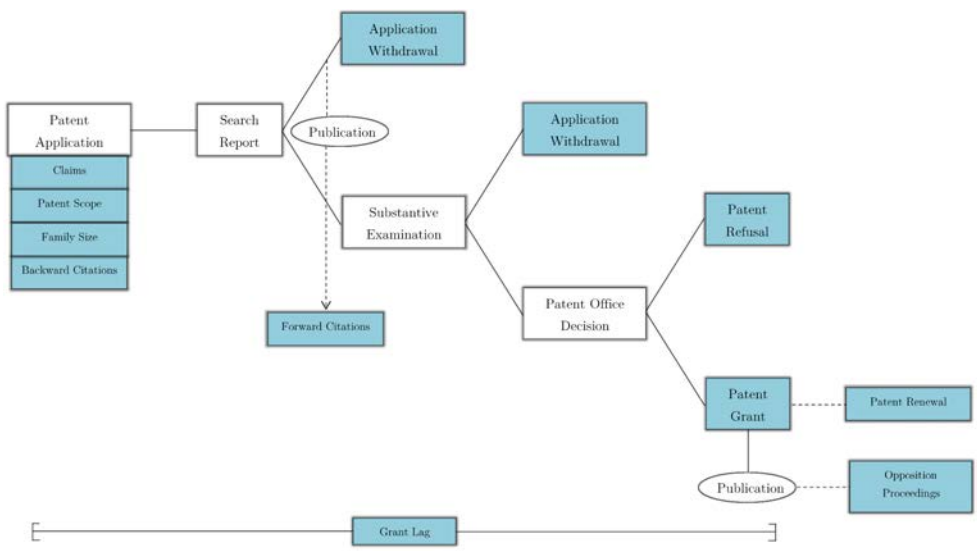


Figure 0.3: Patenting Process Overview

The main advantages of patent data are that they cover a broad range of technologies for which other data sources are often scarce. Furthermore, they have a close link to inventions as most significant inventions from businesses are patented. Each patent document entails detailed information on this inventive process

[5]Notably, the generating commands on the patent measures presented in this paper are in general independent from the subset of chosen patentees and the respective patent applications filed by those firms. Therefore, they can also be applied and utilized in other setups which relate to empirical analyses of patenting activities.

[6]This indicator table, which is referred as the *Indicator_ Table_ Final_ Measures* during the generating process of the patent measures in the respective SQL commands, contains one observation per appln_id and patent measure in its final version. Details on the generating process of this indicator table can be found in subsection 7.3 in line with subsections 7.1 and 7.2 of the appendix.

by referring to previous relevant patents and by giving extensive descriptions on the protected core of the invention. Finally, raw patent data are readily available as patent offices continuously collect a multitude of related data in order to process and evaluate the respective patent applications which facilitates their usage and decreases the associated costs to obtain these data (OECD 2009).

From the above figure, it can be seen that the process for obtaining a patent involves several steps which are similar in all countries (OECD 2009). In a first step, the entity which is looking for patent protection has to file a patent application at a patent office. The applicant needs to disclose the invention in sufficient detail which in particular includes the statement on its *claims*. These contain the aspects of the invention for which the applicant is claiming exclusive rights. Furthermore, each patent document contains information on the technology fields concerned, i.e. the technological domain which a particular invention is attributed to. Given that patented inventions may fall into more than one technological domain, the *patent scope* variable indicates the technological breadth of a patented invention. Finally, each patent application needs to contain citations of previous related patents and scientific literature. These are referred to as the patent's *backward citations*. In the further course of the application process information on the fate of the patent can be obtained. The patent can be *granted* by the patent authority and depending of the length of this granting process the *grant lag* variable can be derived. Alternatively, the grant of the patent can also be *refused* by the patent authority. Besides these outcomes, the patent can also be *withdrawn* by the applicant himself at different stages of the application process. Once published, a filed patent can also be cited by other patent documents, which refers to its *forward citations*. Finally, after a patent is granted, it may be potentially *opposed* by external agents.

3 Patent Measures from Patstat Biblio

This section contains the in-depth analyses to the self-generated patent measures from the Patstat Biblio database for the above described firm-level dataset. Related literature is discussed for each measure in the respective subsections in order to provide the intuition for its relevance in the field of innovation economics. Furthermore, introductory remarks on the utilized information from Patstat as well as on the derived SQL codes - which are discussed and explained at full length in the appendix to this paper - are provided. The descriptive analyses are conducted for each patent measure from multiple perspectives and include time series analyses of means, medians and other relevant quantiles which are derived conditional on firm size classifications, firm country classifications and technological classifications. They are complemented by statistical tests on differences of conditional means as well as by analyses on their conditional distributions. Additionally, multivariate correlation across firm- and invention-related dimensions are conducted for the respective measures.[7]

[7] The patent measures described in the following sections are - to a large extent - self-generated, i.e. most of them are not readily available. In exceptional cases, however, some raw variables of Patstat contain useful information regarding individual patent applications in terms of quantifiable patent measures. Table TLS201_Appl contains information on each patent application which are valuable in this regard. The respective coding in order to import these data into the indicator table can be found in subsection 7.2 in the appendix of this paper. These raw data are also utilized for other patent measures in subsequent subsections of the appendix.

3.1 Grant Lag Measure

The first patent measure to be discussed in this paper is related to the duration of the granting process of patent applications. The grant lag variable is defined as the time frame between the filing date of a patent application and the earliest publication date given that this publication refers to a patent grant. Information about the granting status and the associated grant lag of a patent application are not available in the moment an application is filed, but rather depend on the duration of the granting process as can also be depicted from the figure below.

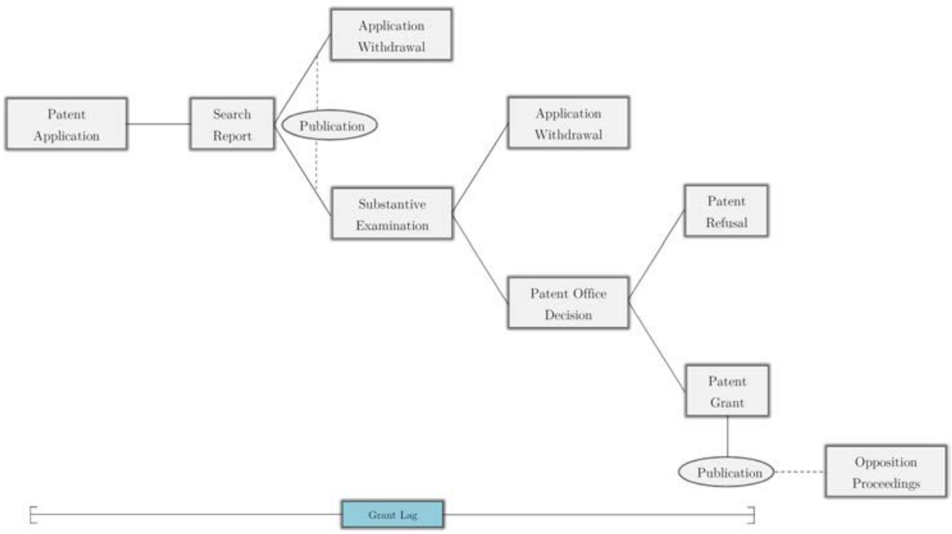


Figure 1.1: Patenting Process Overview

The underlying invention contained in a patent application is only patentable if it is new and previously undisclosed, distinguished by an inventive step not obvious to someone expert in that technology and capable of industrial application (EPO 2017a). Therefore, only technological and commercially applicable inventions can be patented.[8] Along this line, for instance not all patent applications will be granted, because certain applications do not fulfill the above described criteria and only high quality patents which cover significant inventions shall be covered (OECD 2009).

Empirical evidence indicates that the grant lag of a patent application is negatively correlated with the value of a patent and that more controversial claims lead to slower grants (Harhoff and Wagner 2009). Other authors suggest that the effort of the filing party has a negative impact on the duration of the granting process, that more important patents are approved more quickly and that the duration until a patent is granted decreases for industries at later stages of their innovation cycle (Régibeau and Rockett 2010). These findings indicate that higher grant lags are negatively associated with the underlying value of the patented inventions. However, potential increases in workloads of patent offices as well as cross-country differences in certain patent offices display potential weaknesses of measures derived from the grant status of patent applications (Harhoff 2009).

[8]Not every innovation is protected by a patent, either because some innovations cannot be legally protected through patents (e.g. if an the criterion of industrial application is not fulfilled or the innovation is not sufficiently new from a legal point of view), or the innovator deliberately chooses not to protect his innovation and prefers secrecy or open source access over patent protection (Png 2017).

In order to generate the grant lag measure based on the information contained in Patstat Biblio, the variables *appln_filing_date* from the TLS201_appln table as well as the *publn_date* and the *publn_first_grant* variables from the TLS211_pat_publn table are utilized. The application filing date refers to the date on which the application was physically received at the Patent Authority (Chapter 6.7 of the EPO Biblio and Legal Data Catalog). The publication date variable is the date on which a publication regarding a particular patent application was made available to the public (Chapter 6.153 EPO of the EPO Biblio and Legal Data Catalog). Therefore, both dates refer to an individual patent application. The *publication first grant* variable is an indicator variable which indicates whether a publication can be considered as the first publication of a grant of a given application. Therefore, this variable equals 1 if the particular publication step can be considered as the first publication of a grant and 0 otherwise (Chapter 6.154 EPO Biblio and Legal Data Catalog). The codes and further descriptions regarding the generating process of the grant lag variable in SQL can be found in the appendix in subsection 7.5 in line with subsections 7.3 and 7.4.

The following descriptives refer to the patent applications of the firms which can be linked to the Amadeus database based on the matching algorithm provided by Peruzzi et al. (2014). As previously described, multiple applications can be filed by each of the firms included in the Amadeus-Patstat dataset. From the above considerations it can be inferred that the granting procedure of a patent application is time-consuming and requires intermediate formal steps such as the search report and substantive examination at the patent authority before a final conclusion regarding the patent grant is made. The table below depicts annual summary statistics for the self-generated grant lag measure which are based on the information contained in the Patstat database. These findings will be related to considerations from previous literature in the subsequent paragraphs.

Grant Lag - Summary Statistics
[over Year]

j	N	mean	sd	cv	min	max	p25	p50	p75
1995	21486	3.933	2.584	.657	0	19.756	2.132	3.321	5.156
1996	23053	4.151	2.638	.636	.003	19.759	2.17	3.556	5.649
1997	30075	4.531	2.701	.596	0	19.247	2.225	4.258	6.099
1998	34325	4.501	2.622	.583	.052	18.471	2.238	4.214	5.904
1999	38056	4.481	2.698	.602	.068	17.452	2.301	3.986	5.844
2000	42982	4.361	2.562	.587	.071	16.518	2.43	3.868	5.641
2001	43718	4.358	2.545	.584	.058	15.51	2.43	3.882	5.597
2002	49179	4.334	2.507	.578	.058	14.477	2.455	3.874	5.584
2003	48912	4.337	2.463	.568	.058	13.542	2.501	3.773	5.592
2004	55437	4.294	2.374	.553	.074	12.488	2.438	3.8	5.671
2005	65022	4.189	2.327	.555	.066	11.532	2.373	3.797	5.636
2006	65635	4.115	2.28	.554	.052	10.545	2.307	3.838	5.603
2007	64119	3.941	2.079	.527	.06	9.551	2.342	3.734	5.274
2008	53049	3.786	1.87	.494	.047	8.575	2.375	3.586	5.044
2009	41675	3.49	1.723	.494	.112	7.518	2.175	3.337	4.762
2010	36442	3.186	1.502	.471	.104	6.54	2.074	3.17	4.378
2011	29520	2.864	1.26	.44	.025	5.559	2.022	2.923	3.852
2012	26563	2.474	1.014	.41	.011	4.564	1.877	2.562	3.26
2013	16273	1.956	.811	.415	.011	3.537	1.438	2.055	2.542
2014	8699	1.405	.623	.443	.008	2.548	1.107	1.479	1.948
2015	2871	.697	.477	.684	.011	1.553	.148	.764	1.148

Table 1.1

It can be seen that from 1995 until 2009 the grant lag means lie between 3.5 to 4.5 years and the median values between 3.2 and 4.3 years. From 2010 onwards, a sharp decrease in the grant lag mean and median values can be observed which is accompanied by a sharp drop in the number of granted patent applications. These twofold findings can be explained by the fact that the grant lag variable can only be depicted for those firms' patent applications which have already been granted. Consequently, as the current time edge is approached, the total number of granted patents decreases as only those applications with relatively low granting durations contain information regarding their grant lag and are, therefore, included in the summary statistics below. This results in decreases of the mean, median and other percentile outcomes of the grant lag variable. While the number of granted patent applications steadily increased from 1995 until 2006, it is interesting to note that the share of granted patent applications continuously decreased during the same time frame as can be seen from the second table below:

Granted Applications
[Share by Year]

	1995	**1996**	**1997**	**1998**	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**
Grant Share	0.658	0.633	0.599	0.547	0.575	0.562	0.546	0.536	0.510	0.516

2005	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**
0.475	0.467	0.434	0.429	0.440	0.392	0.368	0.287	0.209	0.112	0.058

Table 1.2

The share of granted patent applications lies above 60 percent in the middle of the 1990s, which is consistent with findings from previous literature (Harhoff 2016). Afterwards, it continuously decreases and reaches 47 percent in 2006. These findings are in line with evaluations from the EPO according to which the volume of applications which have to examined follow an upward trend, while the same cannot be said of their quality as incoming filings are not consistent with standards from the European Patent Convention (EPO 2008).

In the beginning of 2008, the EPO introduced a new incentive scheme according to which patent examiners are allowed to assign twice the work points for refusals compared to patent grants (Harhoff 2016). This scheme is based on survey results which found that grant refusals cause about the double work effort compared to the finalization of a grant decision (Friebel et al. 2006). This structural change within the EPO might explain some of the additional decrease in the number and share of granted patent applications from 2008 onwards. As the average granting duration historically lied between four to five years, a substantial part of the decrease in the most current years is, however, attributable to the timeliness of the patent grant process. More research is needed in order to investigate how strong the effect of the newly introduced incentive scheme within the EPO indeed affected patent grant outcomes.[9]

[9] By analogy, the outcomes regarding the normalized grant lag variable outcomes were also analyzed. For the purpose of greater clarity, detailed results regarding the normalized outcomes of the patent measures are however not included in this paper. Normalization was performed in line with previous literature with respect to the maximum outcome per filing year and technological sector (see Squicciarini et al. (2013)). As previously described, the most recent years are characterized by granted patents with short grant lags and comparable durations given that they refer to the same filing year. Thereby, the means of the normalized grant lag outcomes will by construction be relatively close to the maximum grant lag values and result in growing outcomes regarding the evolvement of the normalized grant lag measure as the current time edge is approached.

Following these general considerations regarding the evolvement of the grant lag outcomes, the subsequent set of analyses refers to potential differences of patent grant outcomes relative to the technological areas of the underlying inventions. The classification scheme of patent applications to technology fields is based on the International Patent methodology. According to this scheme, there are 35 IPC classifications, which can be uniquely assigned to one of the following five categorical areas: Electrical Engineering, Instruments, Chemistry, Mechanical Engineering and Other fields (Schmoch 2008). The figure to the right depicts the time series evolvements of the meaned grant lag durations in the five technological areas. In line with the above findings, a sharp drop in the grant lag means can be also observed in all of the five technological areas from 2008 onwards. Besides this shared property of these time series plots, the grant lag outcomes tend to contain structural level differences in the different technological sectors. The time series of the grant lag means for Electrical Engineering, Chemistry and Instruments appear to lie systematically above the time series of Mechanical Engineering and Other Fields. This structural property may be potentially interpreted as support for the the arguments provided by Régibeau and Rockett (2010) according to which durations of patent grants decrease for industries at different stages of their innovation cycle. Building on this, the figure below depicts the evolvement of the grant lag means within four distinct time windows in order to provide the results of an ANOVA test for the equality of the overall grant lag means across the different technological sectors within each of the time frames (1995-1999, 2000-2004, 2005-2009, 2010-2015).

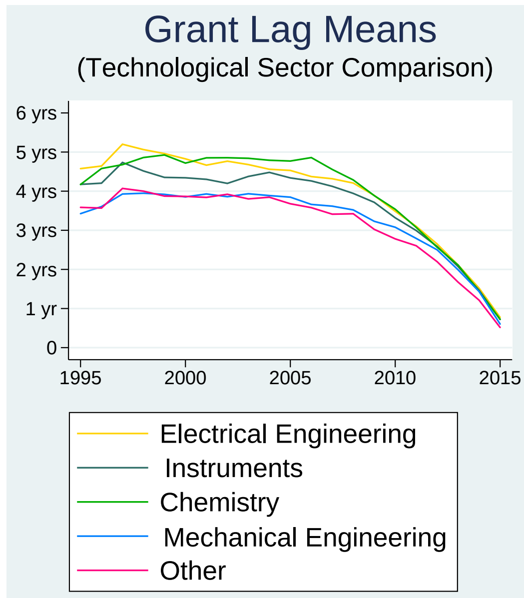


Figure 1.2

The utilized one-way ANOVA is a statistical test to compare the groups given that the outcome variable is continuous and that there are more than two groups (Kao and Green 2008). According to the null hypothesis of this statistical test, the means of the grant lag outcomes should be the same in all five technological areas whilst the rejection of the null hypothesis leads to the conclusion that at least two technological sectors have different means. The test is conducted in each of the four time windows and the respective p-values for the grant lag means of each technological sector are depicted in the figure above. As can be seen, the p-values of this ANOVA test are zero in all four time windows, indicating that the differences of the grant lag means between the technological sectors are statistically highly sig-

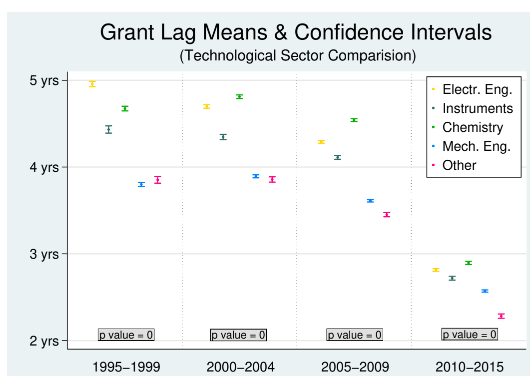


Figure 1.3

nificant. Besides this, the above figure additionally depicts confidence intervals which define the range of values that contain with 95 percent certainty the grant lag population means across the respective technological sectors within each of the the four time windows. With large samples, these means are known with much more precision than with small samples, such that the respective confidence intervals are quite narrow when computed from a large sample, as can be seen from the above figure. The sectors Electrical Engineering and Chemistry have by far the highest grant lag outcomes over time. The corresponding grant lag means confidence intervals from these two technological sectors do not intersect, which indicates that their grant lag means are indeed systematically different. Mechanical Engineering and the other technological sectors have the lowest grant lag means in the four time windows with overlapping confidence intervals between 1995-1999 and 2000-2004. Overall, the above findings indicate that there are significant and highly persistent differences in the duration of patent grants between the technological sectors. These findings are supported by considerations from previous literature. Popp et al. (2004), who take an US perspective, argue based on interviews with patent examiners and conclude that the biggest differences in examination times stem from different technological sectors due to associated differences in complexities of the underlying inventions. These results are also underpinned by their empirical analyses which indicate that applications from newer, more complex technologies such as biotechnology take significantly longer until they are granted than other patent applications. Interestingly, they barely find a difference across mechanical and electrical technologies in their US data, whilst the above descriptive analyses regarding the European patent data depict substantial duration differences between patent grant lags from Mechanical and Electrical Engineering. Cao (2013), who analyzes a set of U.S. patents originating from China, finds that in industries in which the R&D and product cycle is long such as Chemicals, patent applicants would like their patent rights to be long enough to secure revenue. On the other hand, in industries in which the pace of technology is fast and replacements of products happen rather rapidly by more advanced products, patent applicants would like to secure their patent right as soon as possible and lead to faster patent grants. This finding finds support when the distributions of the grant lag outcomes are considered. As can be seen from the violin plots, Chemicals and Electrical Engineering have relatively more mass in their distribution with respect to longer grant durations compared to technological sectors with shorter product cycles such as Mechanical Engineering. In a European context, Harhoff and Wagner (2009) point out that the increasing complexity of patent applications also results in longer pendency times. The summary statistics depicted below provide an technology-focused overview on differences regarding the grant lag outcomes. In line with the above-described considerations, Chemicals ans Instruments have the highest average grant lag duration across all periods, even though the absolute number of patent applications in each of those sectors are smaller

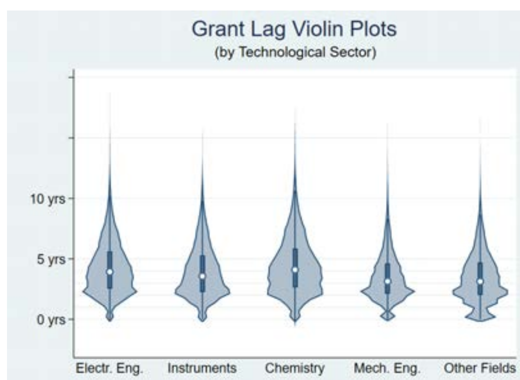


Figure 1.4

than in Mechanical Engineering or the other technological sectors which have substantially lover grant lag outcomes.

Grant Lag - Summary Statistics
[over Technological Sectors]

Sector	N	mean	sd	cv	min	max	p25	p50	p75
Chem.	186589	4.474	2.451	.548	.011	19.49	2.633	4.101	5.841
E.Eng.	181147	4.315	2.328	.539	0	19.759	2.551	3.926	5.614
Instr.	89091	4.024	2.297	.571	.008	18.542	2.279	3.567	5.288
M.Eng.	241239	3.554	2.122	.597	0	19.756	2.126	3.148	4.603
Other	79753	3.458	2.216	.641	0	17.838	2.011	3.132	4.677

Table 1.3

The summary statistics are also in line with the findings from Squicciarini et al. (2013) who analyzed European patent data until 2012 and found that a majority of patents was granted before the seventh year after application, as can be seen from the 3rd quartile outcomes which do not excel six years. More detailed time series evolvements of other percentiles from a technological sector perspective can be found in the appendix to this paper in subsection 6.1.1 which contains time series radar plots of meaned, median and percentile plots over the five different technological sectors.

The next set of descriptives analyzes the grant lag outcomes based on patent applications filed by firms with different sizes. Building on previous considerations, firm-specific information from Amadeus are utilized in order to classify firms into different size categories. Following the classification scheme provided by the European Commission, firms are categorized as i) *small* if they have less than 50 employees and a turnover below 10 mEur, ii) *medium* if they have between 50 and 250 employees and a turnover between 10 - 50 mEur and iii) *large* if they have 250 or more employees and a turnover above 50 mEur.[10] Based on this classification, the summary statistics are depicted below:

Grant Lag - Summary Statistics
[over Firm Size Classifications]

Firms	N	mean	sd	cv	min	max	p25	p50	p75
Large	497765	3.986	2.334	.585	0	19.759	2.236	3.556	5.233
Medium	42021	3.698	2.302	.623	.008	17.4	2.132	3.258	4.899
Small	70554	4.007	2.302	.574	0	18.542	2.244	3.51	5.233

Table 1.4

Harhoff and Wagner (2009) found that that grants and refusals occur earlier for larger applicants and argue that this result is a consequence of sophisticated experience of the large applicants in dealing with the European Patent Office. From the above summary statistics, it can be seen that the overall grant lag mean for patent applications filed by small firms amounts to 4 years which is indeed the highest among the three firm size categories. However, it is surprising to note that the grant lag of patent applications filed by large firms amounts to 3.99 years and lies thereby only marginally below the grant lag duration of small firms. The results of a pairwise t-test show that these differences in the grant lag means of the

[10] See Recommendation of EU-Commission (2003) notified under the document number C(2003) 1422.

applications from the small and large firms are not statistically significant at a one percent significance level. The lowest overall grant lag duration is by far obtained by the medium-sized firms with 3.7 years. In this context, it is interesting to note that by far most overall granted patent applications stem from large firms. Potentially, this aggregated size effect leads to some sort of deficiency in the individual patent application which results in longer average granting procedures for the big amount of patent applications filed by large firms compared to those filed by medium-sized firms.

In order to get a more profound understanding on the grant lag differences across the firm size categories, in a next step the time dimension is also considered. For this purpose and in analogy to the previous analyses, the adjacent figure depicts the evolvement of the grant lag means in the four time windows in order to conduct an ANOVA test for the equality of grant lag means across the different firm size categories.[11] This figure contains the respective p-values of this test as well as the confidence intervals for the 95 percent confidence intervals of the grant lag means within each firm size classification across the time windows considered. It can be seen that the p-values of this test are zero in all four time frames, indicating that the differences of grant lag means between the firm size classifications are statistically highly significant. Furthermore, the respective confidence intervals on the grant lag means allow for pairwise comparisons across the different firm size classifications. Large firms have the highest grant lags outcomes regarding their patent applications in the time frame between 1995 and 2004. From 2005 onwards, both small and large firms had comparable grant lag durations while medium-sized firms consistently had the lowest grant lag durations over the whole time frame.

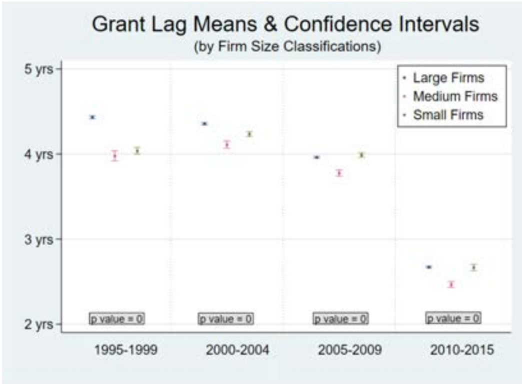


Figure 1.5

These findings are also confirmed by corresponding box plots which additionally depict the corresponding median, their 25th and 75th percentiles as well as their adjacent lower and upper adjacent value based on the respective interquartile range. From this figure, inter alia it can be seen that large firms have consistently higher 75th percentile values and median outcomes compared to the small and medium-sized firms over the four respective time windows. In addition to these figures, the appendix contains more descriptives with the distributional violin plots of the grant lag outcomes in the firm size classifications which can be found in subsection 6.1.2 of this paper.

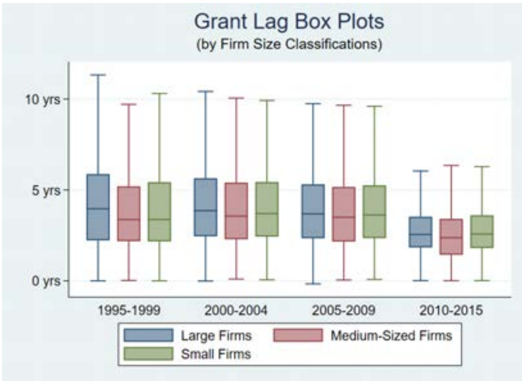


Figure 1.6

[11] The utilized one-way ANOVA is a statistical test to compare the groups given that the outcome variable is continuous and that there are more than two groups (Kao and Green 2008). According to the null hypothesis, the means of the grant lag outcomes should be the same in all firm size classifications whilst the rejection of the null hypothesis leads to the conclusion that at least two firm size classifications have different means.

In the next set of analyses. time series of the grant lag variable based on a country classification regarding the location of the patent filing firms are depicted. The respective summary statistics are depicted below.

Grant Lag - Summary Statistics
[over Firm Country]

Country	N	mean	sd	cv	min	max	p25	p50	p75
AT	22869	3.085	2.032	.659	.014	15.647	1.499	2.679	4.195
BE	23498	4.502	2.469	.548	.019	18.951	2.721	4.167	5.847
DE	226430	3.598	2.389	.664	.003	19.663	1.83	3.252	4.868
FI	32595	4.047	2.433	.601	0	19.756	2.181	3.836	5.49
FR	242622	3.786	2.109	.557	0	19.2	2.214	3.175	4.795
GB	93749	4.365	2.339	.536	.003	19.49	2.737	4	5.584
NL	79199	4.404	2.379	.54	0	19.759	2.679	4.164	5.773
SE	76129	4.431	2.425	.547	.014	18.641	2.545	4.118	5.844

Table 1.5

From the above table, it can be seen that there appear to be substantial differences in the grant lag durations based on differences in the firms' locations. It is important to note that the majority of the patent applications analyzed in this paper stem from so called European Patent applications which are directly filed at the European Patent Office. This constitutes the so called regional route (in contrast to national routes at the national patent offices) in order to seek patent protection. The EPO searches and examines patent applications on behalf of European countries and grants "European patents", which are valid in all its member states in which the holder has validated his rights (OECD 2009).[12] Therefore, differences in grant lag durations as depicted above cannot solely be attributed do potential differences in granting proceedings at the respective national patent offices. These differences are also statistically significant over different time windows as can be seen from the figure that can be found in subsection 6.1.3 in the appendix to this paper. Further figures in the appendix contain histograms and time series plots on the grant lag outcomes across the firm countries and can be found in subsection 6.1.4 of the appendix.

In addition to these analyses, further descriptive figures and tables are contained in the appendix, which provide pairwise correlations of the meaned grant lag outcomes across the above described firm- and technology-specific dimensions. In this vein, subsection 6.1.5 provides insights as to whether and how the grant lag outcomes of the firms' patents are correlated across the firm countries over the three firm size classifications. For this purpose, conditional means on the grant lag durations are generated for each firm country and firm size combination. Based on these conditional means, the correlation coefficients are calculated which contain comparative insights regarding the grant lag evolvements across the firm countries and firm size combinations. Furthermore, the related figures in the appendix also contain the numerical magnitudes of the conditional mean outcomes across these dimensions which allow for determining whether substantial level-differences in the grant lags exist. While these follow-up analyses are rather exploratory in nature, they may contain valuable insights for future research. For instance, the above-established differences in the firms' patents grant lag means for the different firm countries might be partly related to the technological sectors in which the respective patent applications were filed in. These differences

[12] It shall be noted that validation of these patents requires translation into the national language and payment of national fees.

would be observable in the magnitudes of the respective conditional means. Besides this, these differences could also be partly driven by substantial differences in grant durations across the different technological sectors, which would be reflected in low correlation coefficients of the related conditional means. Against this background, these exploratory analyses aim at providing deeper analyses and insights regarding the potential drivers of the above-described results. Subsection 6.1.6. contains the respective descriptive analyses regarding the way the conditional grant lag means of the patent applications filed by firms from different countries are correlated across the technological sectors in which these patents were filed in. Finally, subsection 6.1.7 of the appendix provides deeper insights with respect to the evolvements of the grant lag means as well as the correlation coefficients across firms from different countries and the technological sectors of the corresponding patent filings.

3.2 Patent Claims

The second measure to be discussed in this paper relates to the claims included in a patent document. These give a clear and concise definition regarding the scope of what the patent legally protects. The list of claims depicts the innovative content of the claimed field of exclusivity which, thereby, constitutes the most important part of the patent application. Depending on the number of the claims included in a patent, the associated patent rights are more or less broad (OECD 2009). Larger patents, i.e. with more claims are more expensive and have been found to be adequate predictors of patent value. For instance, Lanjouw and Schankerman (2004) who analyzed US patent data found in their factor model of research productivity that information on the number of claims in the patent application constituted the most important patent indicator of patent quality in almost all technological sectors. It was also shown in literature that patents weighted by their claims are positively related to other measures of national research performance (Tong and Frame 1994). Furthermore, patents with more claims are more likely to be litigated (Lanjouw and Schankerman 2001a).

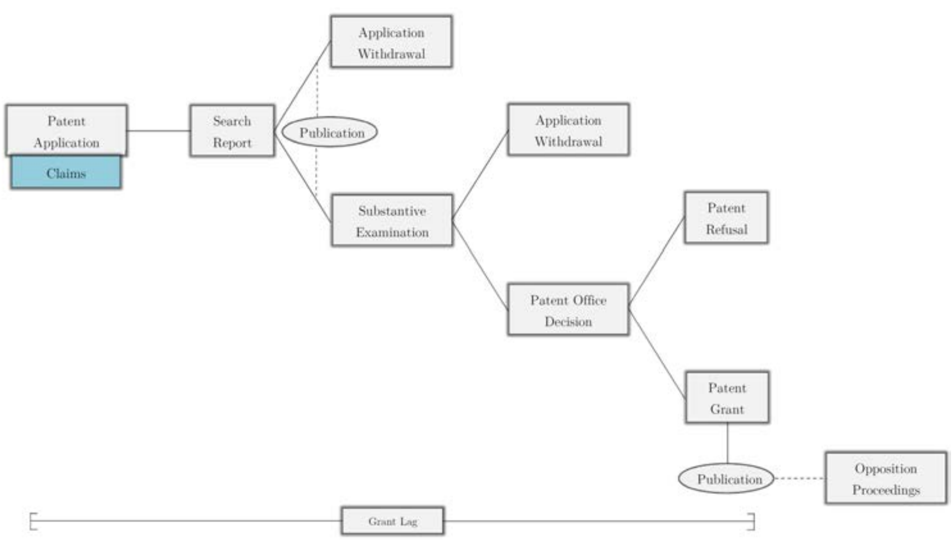


Figure 2.1: Patenting Process Overview

In order to obtain the information on the patent claims from the Patstat Biblio database, the Patstat table

TLS211_Pat_Publn is utilized. This table contains the variable *publn_ claims*. According to Chapter 6.152 of the EPO Biblio and Legal Data Catalog, this variable is an indicator for the number of claims in the given publication. Notably, this variable is only available for certain EP publications. Furthermore, note that the value "0" can mean both, i.e. that either a claim does not contain a claim or that the number of claims is unknown. For instance, the number of claims is "0" for certain EP documents originating from international patent application from the Patent Cooperation Treaty (PCT) which are published in English, French or German whilst for those Euro-PCT documents whose original PCT language is not English, French or German, there is a new publication in one EPO official language and thus the claim count is available.[13] Specifics regarding the coding can be found in subsections 7.6 and 7.4 of the appendix. The subsequent descriptives and figures provide descriptive time series on the evolvement of the claims included in those patent documents which are analyzed in this paper. As documented, these documents refer to the patent applications that can be linked to the Amadeus database based on the matching algorithm provided by Peruzzi et al. (2014). The table below depicts annual summary statistics for the patent claims based on the information contained in Patstat Biblio.

Claims - Summary Statistics
[over Year]

j	N	mean	sd	min	max	p25	p50	p75	p99
1995	8025	10.765	8.135	1	140	5	9	14	40
1996	8551	10.907	8.276	1	174	5	9	14	41
1997	11412	11.355	9.086	1	110	5	9	15	44
1998	13770	11.064	9.064	1	109	5	9	14	46
1999	15018	12.059	9.966	1	164	5	9	16	49
2000	18248	12.259	11.608	1	290	5	9	16	53
2001	18623	9.953	9.156	1	339	5	8	12	42
2002	21535	9.751	8.542	1	330	5	8	12	41
2003	21283	9.041	7.413	1	150	5	7	11	37
2004	26142	9.482	7.167	1	148	5	8	12	36
2005	32747	8.979	6.636	1	124	5	8	11	33
2006	31583	9.266	6.754	1	124	5	8	12	33
2007	32583	9.086	6.549	1	104	5	8	11	33
2008	28527	8.372	5.419	1	131	5	7	11	26
2009	23253	8.157	4.674	1	57	5	7	11	22
2010	22196	8.088	4.678	1	121	5	7	10	21
2011	19511	8.603	5.015	1	137	5	8	11	22
2012	18863	8.758	5.171	1	147	5	8	12	22
2013	12262	9.466	5.271	1	75	6	9	14	23
2014	9541	10.005	5.43	1	56	6	10	15	23
2015	6088	11.036	4.816	1	54	8	11	15	22

Table 2.1

It can be seen that the mean values of claims contained in the subset of the analyzed patent applications from the European firms lie between 8 and 12 claims between 1995 and 2015 and, therefore, contain strong variations over time. Interestingly, the annual means of claims increased from 1995 to 1999 and experienced a sharp drop in 2000. Afterwards, the downward pattern continued until 2010. From 2010 onwards, a strong increase in meaned patent claims can be observed as can also be inferred from the adjacent figure.[14] Building on this, further insights regarding the statistical significance of the differences in the meaned claim

[13] Consequently, the zero values are excluded for means of calculations.

[14] Recall from above, that the descriptives refer to those patent applications with non-zero *publn_ claims* outcomes. Therefore, potential claim effects due to increases in PCT patent filings in German, English and Frensh are not included in these descriptives.

outcomes over time are contained in the following analyses. The development of the average patent claim outcomes from 1995 onwards with their strong decrease between 2000 to 2001 may potentially be related to the burst of the dot-com bubble. This bubble had its origin in the initial public offering by Netscape in 1995 and it found its termination in 2000–2001 with the collapse of the NASDAQ Composite index. It is argued by recent literature that changing market conditions such as the dot-com burst can have a large impact on the value of patent stocks and their derived influence on firm value (Belenzon and Patacconi 2013). By analogy, as patent claims are also used as proxies for patent value, the sharp decreases in average claim outcomes after 2000 (as well as the smooth increase before 1995) may also be partly driven by this bubble. In the same vein, during the recent financial crisis another drop in the average patent claims can also be depicted in the data.[15] Potentially, these fluctuations in the number of claims are to a certain extent also related to associated changes in patent claim fees as a substantially new clams fee schedule took effect in April 2008. Before this change, each claim extending the tenth claim had already been priced at 40 Euro between 1999 to 2006 and at 45 Euro until 2008 (EPO 1999, Archontopoulos et al. 2007). According to the new scheme which became effective in 2008, up to 15 claims are free, while excess claims were charged with 200 Euro each and all claims extending 50 claims amount additional 500 Euro each (EPO 2009). With its new fee structure, the EPO aimed at obtaining less complex patent documents with fewer excess claims by incentivizing applicants to define the protectional scopes of their new incoming patent applications in a clearer and more condensed way (Harhoff 2016).

When the maximum claim outcomes are considered before and after 2008 in the above table, it can be seen that these outcomes have on average become lower after 2008, which provides first indicative support for this aim of the EPO. More importantly, the 99th percentile claim values after 2008 do not exceed 23 and lie substantially below the overall 99th percentile average claim outcome of 36 and consequently far below many of the 99th percentile claim values before 2008. Additionally, the non reported 95th percentile values do not exceed 17 claims after 2008, while the corresponding 95th percentile outcomes lie between 21 and 32 before 2008. These descriptives which refer to the tails of the annual claim distributions provide support that the recent change of the fee structure from 2008 indeed had the desired effects regarding the claim structure of new incoming patent applications by obtaining overall less complex patent applications in terms of decreased excess claim amount outcomes. In this vein, subsequent analyses provide more-detailed distributional plots and analyses of the claim outcomes.

Following these general considerations regarding the evolvement of the claim outcomes, the subsequent set of analyses refers to potential differences of patent claim outcomes relative to the technological areas of the underlying inventions. The classification scheme of patent applications to technology fields is based on the International Patent methodology. According to this scheme, the IPC classifications can be uniquely assigned to one of the following five categorical areas: Electrical Engineering, Instruments, Chemistry, Mechanical Engineering and Other fields (Schmoch 2008). The figure below depicts the evolvement of the

[15] However, it shall be noted that Archontopoulos et al. (2007) who analyze another sample of EPO patent data from 1980-2004 observe constantly increasing claim outcomes until 2004. Therefore, the descriptive findings are likely to be partly driven by the evaluated subset of patent applications. As previously described, the focus of the paper at hand is to provide descriptives for those patent applications which can be linked to the Amadeus database; The selection criteria for the patent documents analyzed in Archontopoulos et al. (2007) remain, however, unclear.

meaned claims in these five technological areas from 1995 to 2015. Interestingly, the shapes of the meaned claim values across the technological sectors evolve very similar and depict the same structural properties as the overall meaned claim time series from above. This provides support that the above-described evolvements of the claim outcomes over time are not driven by technology-specific developments but rather by institutional changes (such as the new fee structure which effects all patent applications from all technological sectors equally) or changes in market conditions (such as the dot-com bubble or the recent financial crisis). Besides this, it is interesting to note that there seem to be differences in levels regarding the average number of claims which are to different degrees persistent over time. For instance, Mechanical Engineering has consistently the lowest average claim outcomes compared to all other technological sectors. Chemical Engineering, on the other hand, had consistently the highest average claim outcomes until 2008. Afterwards, the meaned claim outcomes appear to converge between all technological sectors. These differences in claim levels are also consistent with findings from previous literature. The authors van Zeebroeck et al. (2009) analyze a subset of EPO patent data from 1982 to 2004 and found that industrial specificities have a strong impact on the number of claims included in a patent application. According to them, patent applications from some technological areas such as industrial chemistry are associated with more claims while other sectors such as vehicles and civil engineering had fewer claims and pages. Furthermore, also Archontopoulos et al. (2007) who analyze EPO patent data from 1978 to 2004 find substantial differences in claim sizes between for instance Civil Engineering with substantially lower average claim numbers than Biotechnology.

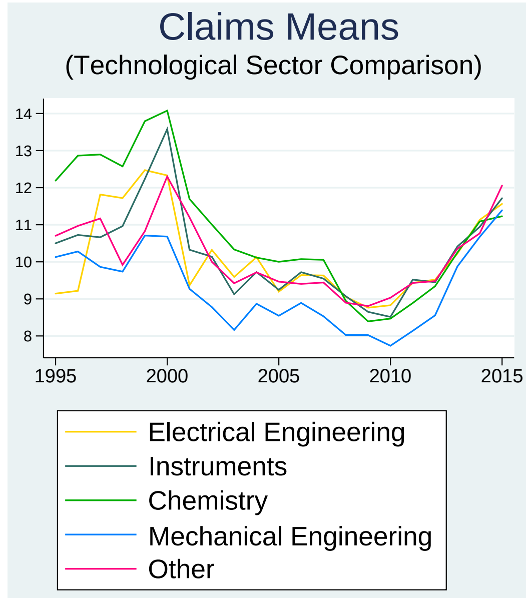


Figure 2.2

Building on this, the subsequent figure depicts the evolvement of the claim means in order to conduct an ANOVA test for the equality of claims means regarding the different technological sectors within four time windows (1995-1999, 2000-2004, 2005-2009, 2010-2015). The utilized one-way ANOVA is a statistical test to compare the groups given that the outcome variable is continuous and that there are more than two groups (Kao and Green 2008). According to the null hypothesis of this statistical test, the means of the claims outcomes should be the same in all five technological areas whilst the rejection of the null hypothesis leads to the conclusion that at least two technological sectors have

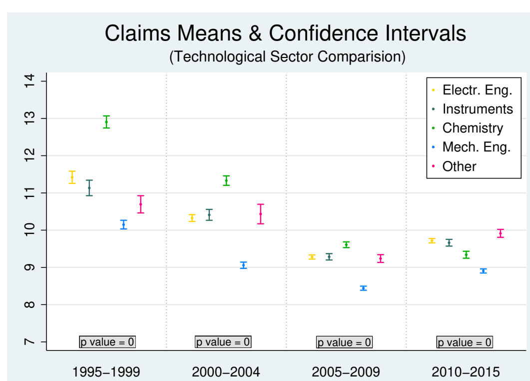


Figure 2.3

different means. The test is conducted in each of the four time windows and the respective p-values as well as additional confidence intervals for the claims means of each technological sector are depicted based on a 95 percent confidence level in the figure above. In line with the previous considerations, it can be seen that the p-values of the ANOVA test are zero in all four time windows, indicating that the differences of the claims means between the technological sectors are indeed statistically highly significant. However, the distributions of the claim outcomes in the respective technological sectors seem to converge as the confidence intervals and mean values in the respective technological sectors lie much closer towards each other between 2005 and 2015 compared to those from 1995 to 2004. These findings are also supported when the overall distributions of the claim outcomes are considered as can be seen from the figure below.

As can be seen from the violin plots, Chemicals have relatively more mass in their distribution with respect more claims compared to the other technological sectors. Furthermore, it can be seen that the distributions for all technological sectors contain peeks at 10 and 15 claims which can be explained by the above-described fee structures over time. Recall that before 2008, each claim extending the tenth claim had already been priced at 40 Euro between 1999 to 2006 and at 45 Euro until 2008 (EPO 1999, Archontopoulos et al. 2007). From 2008 onwards, up to 15 claims are free, while excess claims were charged with 200 Euro each and all claims extending 50 claims amount additional 500 Euro each (EPO 2009). Interestingly, this finding regarding the distributional peaks can also be depicted from the analyses of Squicciarini et al. (2013).

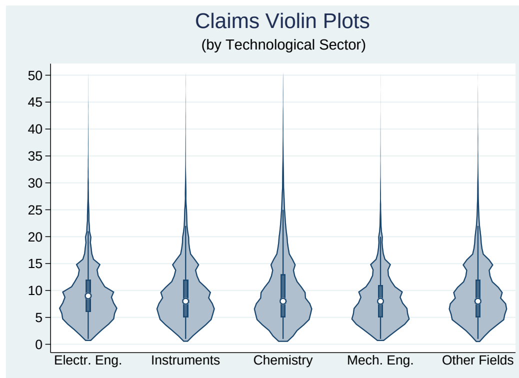


Figure 2.4

The summary statistics depicted below provide an technology-focused overview on differences regarding the claim outcomes. It can be seen that Mechanical Engineering contains overall the smallest meaned claim outcomes with 8.9 claims, whilst the averages of the other technological sectors lie between 9.9 and 10.6 average claims.

Claims - Summary Statistics
[over Technological Sectors]

Sector	N	mean	sd	cv	min	max	p25	p50	p75
Chem.	85106	10.63	8.517	.801	1	230	5	9	14
E.Eng.	111576	9.931	6.955	.7	1	330	6	9	12
Instr.	50927	9.901	7.027	.71	1	150	5	8	13
M.Eng.	107666	8.971	6.151	.686	1	218	5	8	11
Other	30982	9.916	7.77	.784	1	339	6	8	13

Table 2.2

More detailed time series evolvements of other percentiles from a technological sector perspective can be found in the appendix to this paper in subsections 6.2.1 and 6.2.2 which contain inter alia time series radar plots of meaned, median and percentile plots over the five different technological sectors.

The next set of descriptives analyzes the claim outcomes based on patent applications filed by firms with different sizes. In order to classify the firms into size categories, again firm-specific information from the Amadeus database are utilized.[16]

Claims - Summary Statistics
[over Firm Size Classifications]

Firms	N	mean	sd	cv	min	max	p25	p50	p75
Large	255050	9.389	6.931	.738	1	330	5	8	12
Medium	19579	9.557	7.238	.757	1	150	5	8	12
Small	31073	11.542	10.747	.931	1	339	6	9	14

Table 2.3

The summary statistics for this classification are depicted in the table above. Interestingly, the overall average number of claims is much bigger for the patent applications of the small firms compared to those of the medium-sized and large firms. In order to get more profound understanding on claim differences across the firm size categories, in a next step the time dimension is also considered. For this purpose, in a fist step, the meaned claim outcomes are depicted over the three firm size categorizations over time. From the adjoining figure, it can be seen that the meaned claim outcomes of small firms have substantial outliers to the top in 2000 and 2007 compared to medium-sized and large firms. Apart from these outliers, the time series in the three firm size categories evolve relatively comparable. For a more systematic analysis, the next figure depicts the evolvement of the claims means in four different time windows in order to conduct an ANOVA test for the equality of claims means in the different firm size categories within four time windows.The test is conducted in each of the four time windows and the respective p-values as well as additional confidence intervals are depicted for the claims means of each firm size classification based on a 95 percent confidence level in the adjacent figure. It can be seen that the p-values of this test are zero in all four time frames, indicating that the differences of claims means between the firm size classifications are statistically highly significant. Besides this, it can be seen that the confidence intervals for the mean estimates of medium and large firms lie very close together from 2000 to 2015, while the confidence intervals for the mean estimate

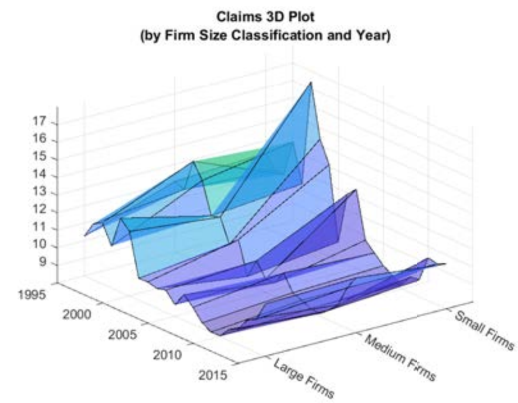


Figure 2.5

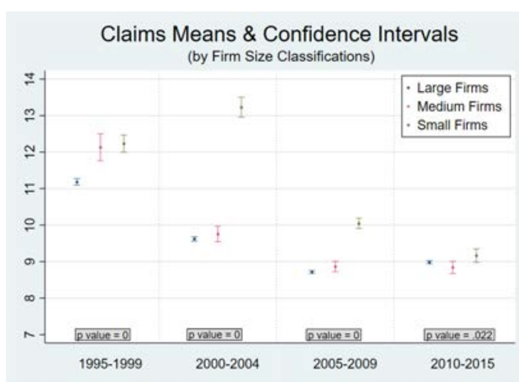


Figure 2.6

[16] Based on the classification scheme provided by the European Commission, firms are categorized as i) *small* if they have less than 50 employees and a turnover below 10 mEur, ii) *medium* if they have between 50 and 250 employees and a turnover between 10 - 50 mEur and iii) *large* if they have 250 or more employees and a turnover above 50 mEur (See Recommendation of EU-Commission (2003) notified under the document number C(2003) 1422).

of the small firms lie considerably above them from 2000 to 2009. Related literature found for a subset of US firms from 1984 to 1994 that the claim stock had a positive and significant effect on the value of firms' knowledge assets while the interaction of firm age and patent claims have a significantly negative impact on these assets (Balasubramanian and Lee 2008). Furthermore, van Zeebroeck et al. (2009) found that inventions that are made by large teams of researchers with complementary skills and expertise seem to require more descriptions and claims in order to be disclosed and protected. Besides this, literature so far provides rather little insights on the the relation of firm size on their patent claims. Consequently, the underlying rationale for the descriptive findings above regarding the differences in claim evolvements - particularly for the subset of small firms - may be a fruitful area for future research. Further descriptives relating to firms' patent claims in context of firm size classifications, including distributional plots as well as boxplots, can be found in subsection 6.2.3 in the appendix of this paper.

In the next set of analyses, the evolvements of the patent claim outcomes based on the country classification regarding the location of the patent filing firms are depicted.

Claims - Summary Statistics
[over Firm Country]

Country	N	mean	sd	cv	min	max	p25	p50	p75
AT	9573	8.761	5.876	.671	1	76	5	8	12
BE	14493	10.339	6.501	.629	1	124	6	9	14
DE	129162	8.859	6.314	.713	1	141	5	8	11
FI	14435	10.102	8.333	.825	1	330	5	9	13
FR	100578	10.148	8.245	.812	1	339	5	8	13
GB	48984	10.145	7.818	.771	1	174	5	8	13
NL	40887	8.454	6.374	.754	1	193	4	7	10
SE	41649	10.023	7.601	.758	1	125	5	8	13

Table 2.4

From the table above, it can be seen that the overall mean claims in all countries lie between 8.5 and 10.3 claims. In order to get a more profound understanding of these differences, the subsequent figures provide time series evolvements of the meaned claim outcomes along the firm country classification.

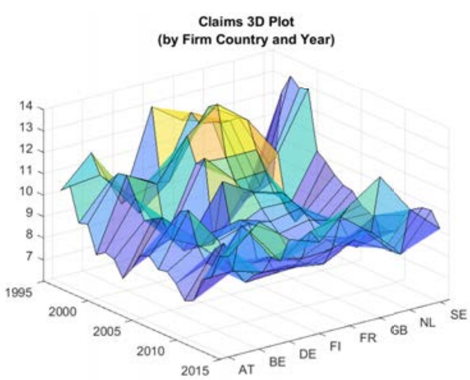


Figure 2.7

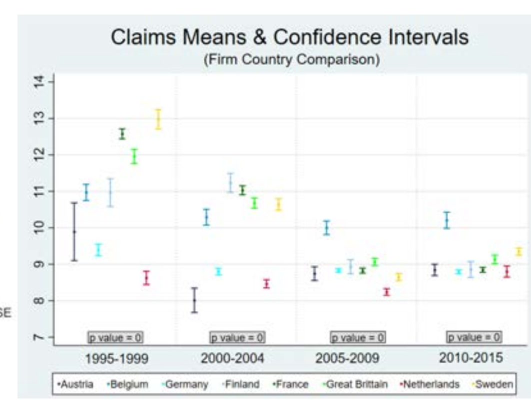


Figure 2.8

While the differences in average claims in the respective time windows are statistically significant over time as can be seen from the above right figure, it is interesting to note that these differences have become substantially smaller in the time frame from 2005 to 2015 compared to the time frame between 1995 and 2004. From a firm-country perspective, previous literature found that in anglo-saxon countries including the United Kingdom as well as in highly specialized countries such as Denmark, applications contain relatively more claims compared to applications from most continental European countries (van Zeebroeck et al. 2009). These two sets of countries essentially differ in as much as they are mainly governed by Common or Civil Law codes. Indeed, in the subset of countries analyzed in this paper, patent applications from Great Britain contain relatively many claims over the analyzed time frame. However, as can be also seen from the above figures, the Scandinavian countries such as Sweden and Finland which are originated in Scandinavian law as well as France and Belgium which have their origins in the Napoleonic Code tend to have relatively high average claims over time.[17]

Building on these findings, the appendix contains further descriptive figures and tables that provide analyses on the pairwise correlations of the meaned claim outcomes across the above-discussed firm- and technology-specific dimensions. While subsection 6.2.5 provides insights as to whether and how the claim outcomes of the firms' patents are correlated across the firm countries over the three firm size classifications in order to obtain a better understanding for the above-described country differences in their claims, subsection 6.2.6. contains analogous descriptive analyses regarding the way the conditional claim means of the patent applications filed by firms from different countries are correlated across the technological sectors in which these patents were filed in. Finally, subsection 6.2.7 contains insights with respect to the evolvements of the claim means across firms from different countries and the technological sectors of the corresponding patent filings. The related figures which are included in these subsections also provide the numerical magnitudes of the conditional mean outcomes across these dimensions which allow for determining whether substantial level-differences in the claim outcomes exist. These additional exploratory analyses aim at providing deeper analyses and insights regarding the potential drivers of the above-described results.

3.3 Patent Scope

As a next measure, the patent scope variable, which captures the number of technical classes that are attributed to a patent, is discussed. This variable measures the technological breadth of a patent application by counting the distinct International Patent Classes included in an application. The pioneering work by Lerner (1994) found a positive correlation between the market value of a firm and its average patent scope in a US context and, thereby, provided empirical support to the theoretical framework by Klemperer (1990), according to which the marginal value of the patent scope is higher when there are many substitutes in the same product class. Also Reitzig (2003) argued in his exploratory study on semiconductor firms that patent scope is a value driver, as well as van Zeebroeck and Van Pottelsberghe de la Potterie (2011). Given that inventions can be considered to be combinations of existing ideas, the wider the set of ideas in terms of technological classes covered, the more valuable a patent is (Guellec and Van Pottelsberghe de La Potterie 2007, Dechezleprêtre et al. 2017). A survey analysis conducted by Harhoff et al. (2003) on

[17] A histogram plot of the patent scope outcomes across the firm country classifications can be found in the appendix of this paper in subsection 6.3.4.

the perceived economic value of patents by German inventors, however, did not find the patent scope to be indicative for the patent value in none of the analyzed technology fields. Based on recent empirical findings, Mastrogiorgioa and Gilsing (2016) suggest that a higher patent scope may block more incremental innovations while stimulating exaptive innovations which potentially form precursors of more radical innovations. Other studies found that a broader patent scope is associated with a higher likelihood of a licensed invention being commercialized as a product (Dechenaux et al. 2008). Furthermore, the results by Nerkar and Shane (2003) showed that start-ups which had classified patents in a higher number of classes were less likely to fail, while this effect is reduced in more concentrated industries, in which marketing and manufacturing agreements are relatively more important for a firm's survival (see also Novelli (2015)). Finally, Lanjouw and Schankerman (1997) found for US patent case filings that patents which were classified in a higher number of international patent classes are associated with a lower probability of litigation.[18]

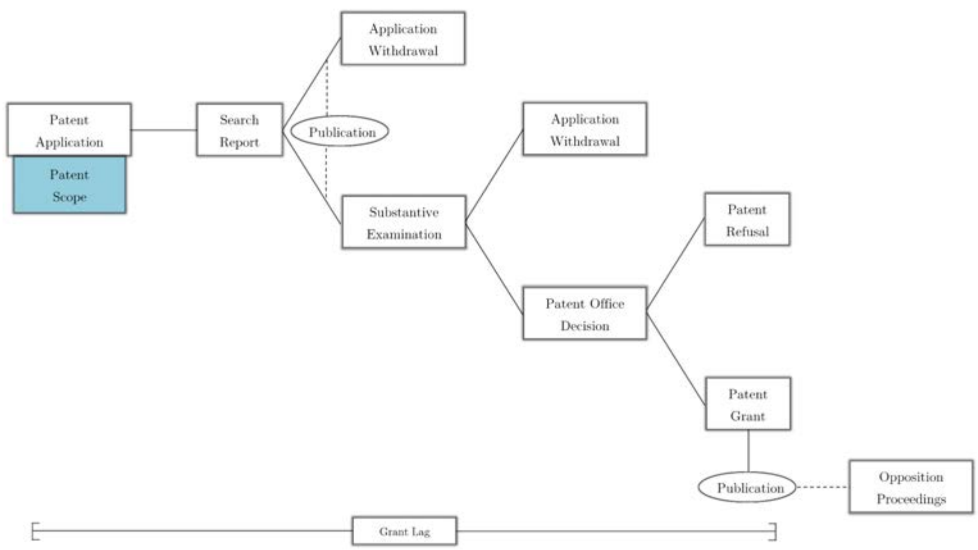


Figure 3.1: Patenting Process Overview

The International Patent Classification (IPC) is based on Standard ST. 8 of the World Intellectual Property Organization (WIPO) and consists of the first 4 to 8 characters of an IPC class symbol (see Chapter 6.77 and 6.79 of the EPO Biblio and Legal Data Catalog). The primary objective of the IPC is - by means of obtain an internationally uniform classification of patent documents - to establish an effective search tool for the retrieval of patent documents by intellectual property offices and other users. Furthermore, the IPC creates a basis in order to investigate the state of the art in a given field of technology as well as for the preparation of industrial property statistics which permit the assessment of technological development in various areas (see WIPO 2018a). The first four symbols of the IPC class (i.e. IPC4) refer to the section, class and subclass of the hierarchical levels in order to categorize patents for inventions. Sections refer to the highest level of the hierarchy. The section title constitutes a very broad indication of the contents of the section and is designated by one of the capital letters A through H. (see Chapter 2 of the layout description in the Guide to the International Patent Classification (WIPO 2018a). The eight sections define the following categories:

[18]A more sophisticated body on literature which refers to theoretical as well as empirical considerations on the patent scope measure can be found in (Lanjouw and Schankerman 1997).

A	Human Necessities
B	Performing Operations; Transporting
C	Chemistry; Metallurgy
D	Textiles; Paper
E	Fixed Constructions
F	Mechanical Engineering; Lighting; Heating; Weapons; Blasting
G	Physics
H	Electricity

The second hierarchical level of the IPC classification is the class. Each class symbol consists of the section symbol followed by a two digit number. The third hierarchical level is the subclass, which consists of the class symbol followed by a capital level. The IPC4 classification therefore refers to the third hierarchical level of the IPC classification scheme. The information regarding the IPC classifications are covered in the TLS209_Appln_Ipc table. According to Chapter 5.8 of the EPO Biblio and Legal Data Catalog, the set of classifications linked to a single application is a de-duplicated merge of all classifications of the various publication instances linked to the specific application. Concretely, this translates into the following procedure described in the Business Rules of Chapter 5.8: if multiple publications regarding one patent application contain the same IPC class symbol, only the highest IPC class level is considered regarding this IPC class symbol. If multiple publications regarding the same patent application also share the same IPC class level, the IPC from the latest publication takes precedence. Importantly, only the latest version of IPC classifications is used and older applications will also be classified according to the latest IPC version. The latest versions of IPC codes can be found in the Guide to the International Patent Classification (WIPO 2018a), which is regularly updated by the WIPO. The structure of the TLS209_Appln_Ipc table is such that each row contains one distinct *ipc_class_symbol*. Therefore, regarding one application id, numerous entries with multiple IPC class symbols may occur. In order to calculate a patent scope measure for individual patent applications, distinct IPC classifications are counted per patent application based on the first 4 digits of the IPC classification on patent application level. Following the above descriptions regarding the use of the IPC classification to assess the technological development in patent documents, this measure can be considered as being indicative with respect to the technological breadth of the invention. Specifics regarding the generating process of the patent scope IPC4 measure can be found in subsection 7.7 of the appendix.

The subsequent descriptives and figures provide descriptive time series on the evolvement of the patent scope outcomes included in those patent documents which are analyzed in this paper based on the firm-level Amadeus-Patstat dataset. In this vein, the table below depicts the annual summary statistics for the patent scope values contained in the firms' patent applications derived from the information contained in Patstat Biblio.[19] From this table, it can be seen that the mean patent scope values contained in the patent documents lie between 1.6 and 2.2 between 1995 and 2015. The numerical variations in the meaned patent

[19]Therefore, the column "N" in the table below refers to the the number of the firms' patent applications based on which the patent scope descriptives are generated. As previously described, the distinct IPC classifications are counted for each patent application such that the respective patent scope outcomes are provided on individual patent application level.

scope outcomes are therefore relatively low in the considered time frame. However, it is interesting to note that in the mid-2000s a downward level shift in the meaned patent scope values can be observed. This pattern of the IPC4 patent scope outcomes is consistent with findings from previous literature (Squicciarini et al. 2013).

Patent Scope - Summary Statistics
[over Year]

j	N	mean	sd	min	max	p25	p50	p75	p99
1995	32590	2.121	1.324	1	11	1	2	3	7
1996	36351	2.037	1.266	1	15	1	2	3	6
1997	50121	2.053	1.393	1	21	1	2	3	7
1998	62604	2.011	1.233	1	21	1	2	3	6
1999	65923	2.072	1.27	1	14	1	2	3	7
2000	75932	2.122	1.317	1	30	1	2	3	6
2001	79573	2.077	1.278	1	30	1	2	3	6
2002	90740	2.047	1.226	1	25	1	2	3	6
2003	95052	2.01	1.183	1	30	1	2	3	6
2004	106050	1.911	1.106	1	17	1	2	2	6
2005	133877	1.802	1.042	1	15	1	2	2	5
2006	138053	1.702	.95	1	30	1	1	2	5
2007	144358	1.677	.93	1	14	1	1	2	5
2008	120106	1.675	.926	1	11	1	1	2	5
2009	92373	1.706	.945	1	13	1	1	2	5
2010	90289	1.693	.947	1	13	1	1	2	5
2011	77974	1.689	.943	1	11	1	1	2	5
2012	90589	1.66	.925	1	19	1	1	2	5
2013	76249	1.649	.89	1	10	1	1	2	5
2014	76477	1.611	.864	1	18	1	1	2	4
2015	48500	1.635	.891	1	17	1	1	2	5

Table 3.1

One rationale for this drop can be found in the fact that, according to the World Intellectual Property Organization, the IPC classification scheme is periodically revised in order to improve the system as well as to take into account changes in technical developments (WIPO 2018a). In 2006, a substantial revision of the IPC system took place, which introduced a much broader set of classification codes. While previous IPC systems were conceived in a period where international trade was focused on a small number of industrial countries, the relevance of emerging countries increased in the last decade, so that an appropriate technology classification system was needed which allowed for international comparisons by taking into account a much broader set of countries (Schmoch 2008). In accordance with the so derived new IPC codes, patents based on previous IPC systems, i.e. before 2006, had to be re-classified in order to obtain a consistent IPC classification framework. Due to the emergence of new technologies, a one-to-one correspondence between the old and new IPC editions did not exist sometimes and older IPC codes might correspond to more IPC codes from the 2006 revision, thereby providing an explanation for the higher IPC averages before 2006 (Squicciarini et al. 2013). Besides these developments of the meaned outcomes, the maximum patent scope values as well as the other percentile moments are also (much) lower after 2006 compared to the period from 2006 backwards.

Following these general considerations regarding the evolvement of the patent scope outcomes, the subsequent set of analyses refers to potential differences of patent scope values relative to the technological areas of the underlying inventions. The classification scheme of patent applications to technology fields is based on the International Patent methodology (Schmoch 2008). The figure belog depicts the evolvement of the meaned patent scope values in five technological areas from 1995 to 2015. Interestingly, the shapes of the meaned patent scope values across the technological sectors evolve similar and depict the same structural properties as the overall meaned patent scope time series values discussed above. This finding provides support for the argument that the above-described evolvements of the patent scope outcomes are not driven by technology-specific developments, but rather by the institutional change in terms of the new IPC classification system due to its impact on all patent applications from different technological sectors. Besides this, it is interesting to note that there seem to be time persistent differences in levels regarding the average patent scope values between the technological sectors. In particular, the patent scope outcomes in Chemistry are substantially higher than in all other technological sectors.

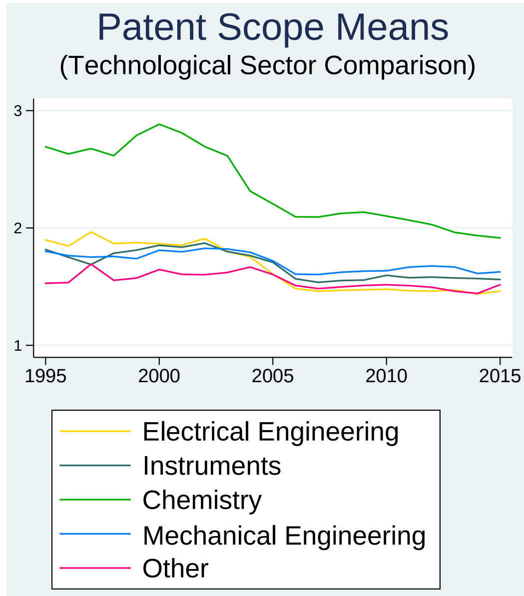


Figure 3.2

In this context, literature points out that the IPC classes are complex and vary in their granularity across technologies (Kuhn and Thompson 2017). Furthermore, previous literature found that firms in the chemical industries seemingly own European inventions of large technological breadth in terms of their patent scope (see Dernis et al. (2015)), potentially because the related patents in this industry embed more complex technologies (Czarnitzki et al. 2012). From this background, the numerical differences in patent scope outcomes referring to Chemistry compared to other technological sectors become understandable. These descriptives are also in line with distributional findings from previous literature (Squicciarini et al. 2013). Building on this, the subsequent figure depicts the evolvement of the patent scope means in order to conduct an ANOVA test for the equality of patent scope means regarding the different technological sectors within four time windows (1995-1999, 2000-2004, 2005-2009, 2010-2015). According to the null hypothesis of this statistical test, the means of the patent scope outcomes should be the same in all five technological areas whilst the rejection of the null hypothesis leads to the conclusion that at least

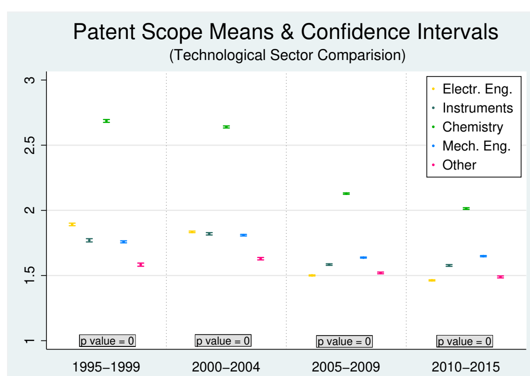


Figure 3.3

two technological sectors have different means. The test is conducted in each of the four time windows and the respective p-values are depicted in the figure. Not surprisingly, it can be seen that the p-values of the ANOVA test are zero in all four time windows, indicating that the differences of the patent scope means across the technological sectors are indeed statistically highly significant, particularly when the Chemistry sector is considered. Besides this, the figure also contains additional confidence intervals which define the range of values that contain with 95 percent certainty the patent scope population means across the respective technological sectors within each of the the four time windows. With large samples, these means are known with much more precision than with small samples, such that the respective confidence intervals are quite narrow when computed from a large sample, as can be seen from the figure above. Aside from the Chemistry sector, the confidence intervals of the remaining technological sectors indicate that the meaned patent scope outcomes differ between the other technological sectors as well, while the relative order between the technological sectors changes over time. For instance, Electrical Engineering has higher patent scope outcomes from 1995 until 2004 relative to Mechanical Engineering, while this picture changes from 2005 until 2015.

These findings are also supported when the overall distributions of the patent scope outcomes are considered as can be seen from the figure below. From the violin plots below it can be seen that Chemicals have relatively more mass in their distribution with respect higher patent scope outcomes compared to the other technological sectors. Furthermore, it can be seen that the plots of the remaining technological sectors look quite similar. Besides this, no further differences in the overall distributions of the patent scope outcomes can be established. Finally, the summary statistics depicted below provide an technology-focused overview on differences regarding the patent scope outcomes. In line with the above considerations, it can be seen that the overall mean outcomes in the Chemicals sector are substantially higher than in the other technological sectors and they also contain higher median as well as third quartile values compared to the remaining technological sectors.

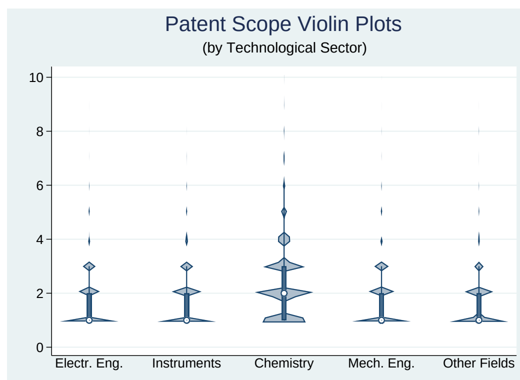


Figure 3.4

Patent Scope - Summary Statistics
[over Technological Sectors]

Sector	N	mean	sd	cv	min	max	p25	p50	p75
Chem.	457629	2.329	1.301	.559	1	21	1	2	3
E.Eng.	449159	1.63	.949	.582	1	30	1	1	2
Instr.	210988	1.66	.93	.56	1	11	1	1	2
M.Eng.	508662	1.697	.955	.563	1	18	1	1	2
Other	155993	1.548	.843	.544	1	13	1	1	2

Table 3.2

More detailed time series evolvements of other percentiles from a technological sector perspective can be found in the appendix to this paper in subsections 6.3.1 and 6.3.2 which contain inter alia time series radar plots of meaned, median and percentile plots as well as histogram plots over the five different technological sectors.

The next set of descriptives analyzes the patent scope outcomes based on patent applications filed by firms with different sizes. Based on the classification scheme provided by the European Commission, firms are categorized as i) *small* if they have less than 50 employees and a turnover below 10 mEur, ii) *medium* if they have between 50 and 250 employees and a turnover between 10 - 50 mEur and iii) *large* if they have 250 or more employees and a turnover above 50 mEur.

Patent Scope - Summary Statistics
[over Firm Size Classifications]

Firms	N	mean	sd	cv	min	max	p25	p50	p75
Large	1121336	1.815	1.061	.585	1	30	1	2	2
Medium	86906	1.832	1.065	.581	1	15	1	2	2
Small	137632	2.052	1.253	.611	1	21	1	2	3

Table 3.3

In the table above, the summary statistics for this size classification scheme are depicted. It appears interesting that the overall average patent scope value is the highest for the patent applications of the small firms compared to those of the medium-sized and large firms. In order to get more profound understanding on patent scope differences across the firm size categories, in a next step the time dimension is also considered. Therefore, in a first step, the meaned patent scope outcomes are depicted over time for the three firm size categorizations. It can be seen from the adjoining figure, that the meaned patent scope outcomes of small firms seem to be consistently higher relative to those of the medium-sized and large firms. Apart from this, the time series shapes in the three firm size categories evolve relatively alike. The next figure depicts the evolvement of the patent scope means in four different time windows in order to conduct an ANOVA test for the equality of patent scope means in the different firm size categories within four time windows.

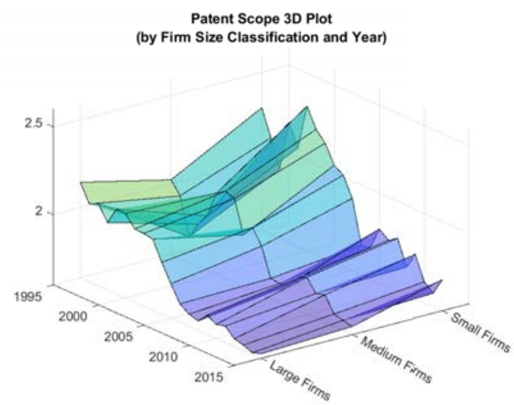


Figure 3.5

It can be seen that the p-values of this test are zero in all four time frames, indicating that the differences of patent scope means between the firm size classifications are statistically highly significant. Besides this, it can be seen that the confidence intervals for the mean estimates of medium and large firms lie rather close together from 2000 to 2015, while the confidence intervals for the mean estimate of the small firms lie considerably above them from 1995 to 2015. Literature so far provides rather little insights on the the relation of firm size on the scope of their patents. According to recent empirical findings, Mastrogiorgioa and Gilsing (2016) suggest that a higher patent scope may block more incremental innovations while stimulating exaptive innovations which potentially form precursors of more radical innovations.

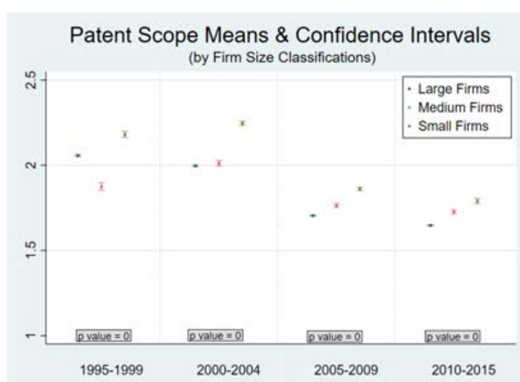


Figure 3.6

Furthermore, larger firms are perceived to focus more on incremental research than innovative research (Coughlin 2012, Barnett 2004). It is argued that large firms have an incentive to incrementally improve and debug their existing innovations, but less incentives to undertake more expensive and risky innovative activities that are more likely to render the large firm's existing innovation obsolete (Coughlin 2012). From this viewpoint, lower patent scope outcomes of larger firms could be expected. Along these lines, the above-described results regarding the patent scope outcomes of firms from different size classifications appear plausible, as the the meaned patent scope values of the larger firms are indeed systematically lower over time than the corresponding outcomes of the small firms. Apart from this, the underlying rationale for the descriptive findings above regarding the differences in patent scope evolvements across the different firm size classification constitute a fruitful area for future research. More descriptive evidence relating to firms' patent scope outcomes in context of firm size classifications, including distributional plots as well as boxplots, can be found in subsection 6.3.3 in the appendix of this paper.

The next set of analyses depicts the time series of patent scope outcomes based on the country classification regarding the location of the patent filing firms. The respective summary statistics can be found in the table below.

Patent Scope - Summary Statistics
[over Firm Country]

Country	N	mean	sd	cv	min	max	p25	p50	p75
AT	43725	1.683	.973	.578	1	10	1	1	2
BE	51356	1.993	1.25	.627	1	15	1	2	3
DE	575275	1.713	.985	.575	1	24	1	1	2
FI	67057	1.839	1.08	.587	1	13	1	2	2
FR	450069	1.9	1.15	.605	1	30	1	2	2
GB	222650	1.951	1.166	.597	1	30	1	2	3
NL	201722	1.854	1.118	.603	1	19	1	2	2
SE	171927	1.782	.997	.559	1	13	1	2	2

Table 3.4

From this table, it can be seen that the overall patent scope means lie between 1.68 and 1.99 in all countries and are, therefore, very close to each other. In order to get a more profound understanding of the cross-country differences, the subsequent figures provide time series evolvements of the meaned patent scope outcomes along the firm country classification.

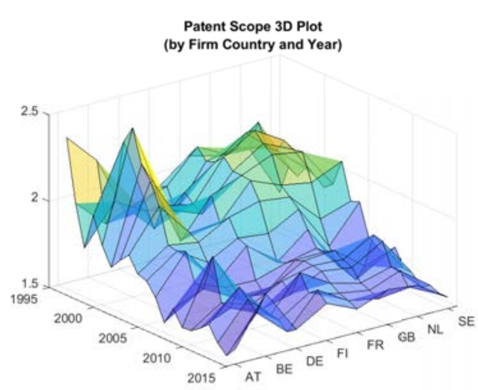


Figure 3.7

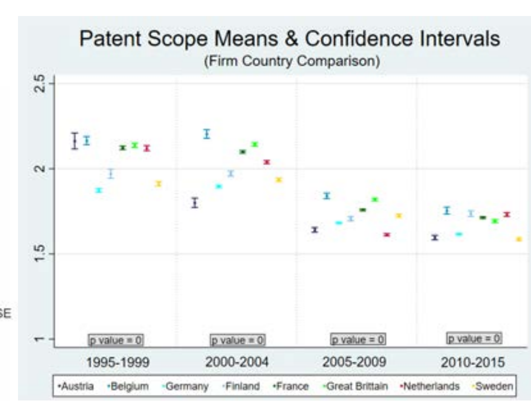
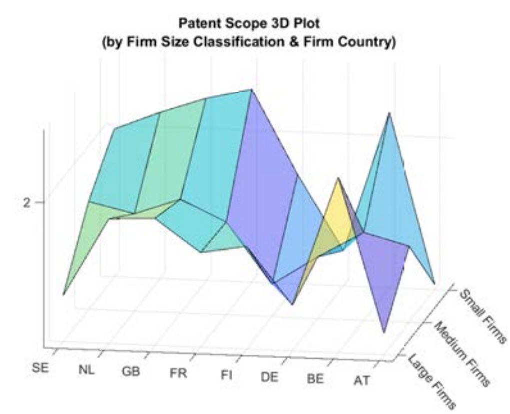


Figure 3.8

The differences in average patent scope outcomes are statistically significant over time in the respective time windows as can be seen from the above right figure. Interestingly, these differences appear to have become smaller in the time frame from 2005 to 2015 compared to the time frame between 1995 to 2004.

In order to obtain more sophisticated insights on these cross-country differences in the firms' patent scope outcomes, the following analyses provide further insights regarding the pairwise correlations of the meaned patent scope outcomes across the above described firm- and technology-specific dimensions. In this vein, the following figure provides insights as to whether and how the patent scope outcomes of the firms' patents are correlated across the firm countries over the three firm size classifications. For this purpose, conditional means on the patent scope outcomes are calculated for each firm country and firm size combination. These conditional means are utilized in order to estimate the correlation coefficients which contain comparative insights regarding the patent scope evolvements of the conditional patent scope means across the firm countries and firm size combinations. Besides this, the figure below also contains the numerical magnitudes of the conditional mean outcomes across these dimensions which allow for determining whether substantial level-differences in the patent scope outcomes exist. A high pairwise correlation of the patent scope outcomes across large and medium firms would, for instance, imply that large and medium-sized firms are affected similarly regarding their patent scope outcomes across the different countries in which these firms are located in.



Patent Scope - Pairwise Correlations
[over Firm Country]

Variables	(1)	(2)	(3)
(1) Large Firms	1.000		
(2) Medium Firms	0.186	1.000	
(3) Small Firms	0.747*	0.558	1.000

Figure 3.9

It can be seen that the pairwise correlation values of the meaned patent scope outcomes are positive between all three firm size classifications over the different firm countries.[20] The correlation is very high

[20]A star in the table would indicate significance at the 5 percent level.

and statistically significant between small and large firms such that it can be inferred that large and small-sized firms are affected very similar in their patent scope outcomes irrespectively of the countries in which these firms are located in. The patent scope outcomes of medium sized firms are, however, characterized by a relatively small and insignificant correlation with large firms, indicating that patent scope outcomes between large and medium firms have different outcomes across the countries analyzed. While the patent scope outcomes of the small firms lie systematically above those from large firms as can be seen from the figure above, they tend to evolve similarly across the different firm countries which indicates that firms' location tends to have some systematic impact on the their patent scope. These findings are interesting in context of the above-described considerations from previous literature, according to which large firms have an incentive to incrementally improve and debug their existing innovations, but less incentive to undertake more expensive and risky innovation which would be more likely to undermine their existing innovation stock (Coughlin 2012). The underlying driver for these differences in patent scope levels across different countries are, however, unclear at this stage. More research is needed in order to get a more profound understanding of the cross country differences in patent scope levels as well as cross country similarities between the firm size categories. In this vein, the descriptives contained in subsection 6.3.5 change the perspective and analyze whether the conditional patent scope means for firms of different sizes are correlated over the firm-country locations. Furthermore, subsection 6.3.6 depicts analogous descriptives regarding the way the conditional patent scope means of the patent applications filed by firms from different countries are correlated across the technological sectors in which these patents were filed in. Finally, subsection 6.3.7 of the appendix provides deeper insights with respect to the evolvements of the grant lag means as well as the correlation coefficients across firms from different countries and the technological sectors of the corresponding patent filings.

3.4 Family Size

The next measure to be discussed in this paper relates to the geographical scope of patent protection, more precisely the number of patent office jurisdictions in which a patent grant is sought. This measure is referred to as the geographical family size.[21] Based on the Paris Convention from 1883, applicants have up to 12 months from the first filing of a patent application in order to seek for patent protection in other jurisdictions and the right to claim the priority date of the first application (Squicciarini et al. 2013). In context of patents filed at the EPO, the applicants list those countries in which patent protection is sought

[21] One alternative measure relates to the simple number of countries is in which patent protection is sought, see de Rassenfosse et al. (2014). Another alternative measure relates to the *DOCDB family size*. According to Chapter 6.39 of the EPO Biblio and Legal Data Catalog every patent application belongs to exactly one DOCDB family. DOCDB constitutes the EPO's master documentation database with worldwide coverage. The rationale behind this family size categorization is that if two applications claim exactly the same prior applications as priorities (which can be e.g. Paris Convention priorities or technical relation priorities), these applications are defined by the EPO to belong to the same DOCDB family. The more applications belong to the same DOCDB family, the higher the DOCDB family size of a particular patent application will be. Therefore, this measure may be interpreted as an indication with respect to how similar a particular patent application is compared to other patent applications. The higher the DOCDB family size variable is the more patent applications exist with respect to similar priorities or technical relations. However, it appears rather difficult to make deductions on patent-specific dimensions relating to the value of the underlying inventions based on this broad family size measure, while the geographic family size measure contains patent-specific value-related information as can be inferred from the subsequent considerations of this subsection. Apart from this, various definitions and ways to measure patent families exist (see Martínez (2011)).

for. As the publication authority for these patent applications is the EPO, the countries mentioned in them are attributed to the this patent office for means of generating the family size measure (de Rassenfosse et al. 2014). This EP patent application needs to be validated by the different national offices in order to establish the final bundle of national patents (Squicciarini et al. 2013).[22] From these consideration it follows, that the geographical family size as defined here reports the number of distinct patent offices and not the number of distinct countries per see.[23]

Previous literature found that patent value is associated with the geographical scope of patent protection, since the decision to protect an invention at different patent offices reflects the willingness of the owner to bear the costs of international patent protection (OECD 2009, Putnam 1997). Also Harhoff et al. (2003) found in their survey analysis of German held patents that family size is correlated with estimates of the value of patent rights. Furthermore, Lanjouw and Schankerman (2004) found in an US setup that there is a a strong positive relationship between a patent quality index and their family size. Finally, from a European perspective, a positive relation between patent family size and the likelihood of the European patent to be granted could be established (Guellec and van Pottelsberghe de la Potterie 2000). Based on these considerations, information on patent families are used by researchers as proxies for patent value. As family size is comparable internationally and contains information regarding the value of a patented invention, this measure is well suited for studies which rely on patent applications that are filed in different jurisdictions (de Rassenfosse et al. 2014). In this vein, other related literature has shown that patents filed at different patent offices are a good indicator of countries' research productivity (de Rassenfosse and van Pottelsberghe de la Potterie 2009).

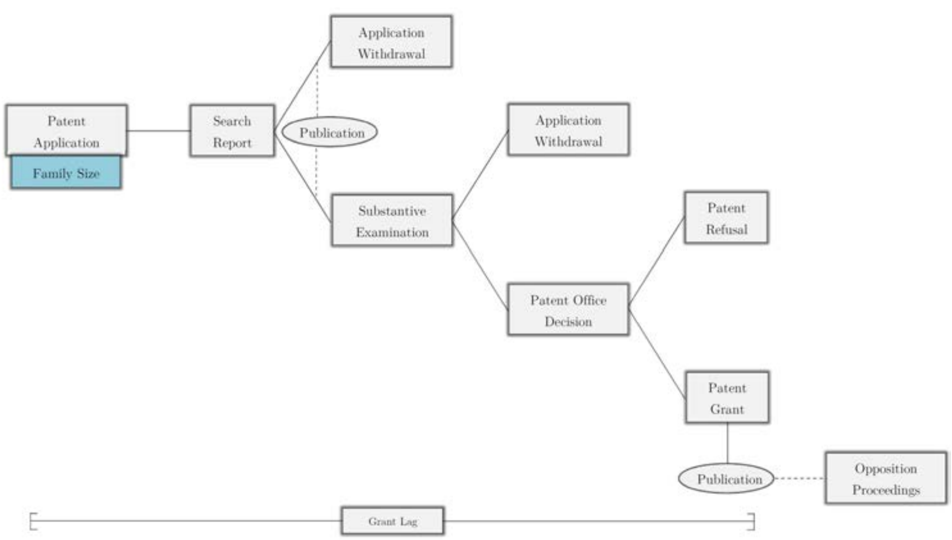


Figure 4.1: Patenting Process Overview

[22]The geographical family size measure is per construction smaller if a patent application is filed via the regional route at the EPO compared to the national route at each individual national patent office (OECD 2009, de Rassenfosse et al. 2014). The underlying reasons for inventors to file via the national versus the regional route are multifold and may have procedural and patent strategy reasons (see de Rassenfosse et al. (2014) for more details). Comparative analyses which provide insights as to how the family size outcomes differ if all patent applications that are directly or indirectly linked via priority filings and, therefore, go beyond the filings at different patent offices are provided in subsequent parts of this section.

[23]More insights regarding potential improvements of this family size classification can be found in de Rassenfosse et al. (2014).

In order to generate the geographic family size measure, variables from both, the TLS211_Pat_Publn table as well as from the TLS201_Appln table are utilized. Based on these datasets and in line with the considerations above, information on the patent offices of destination, more precisely the publication authorities of the INPADOC family members, are extracted (de Rassenfosse et al. 2014, Squicciarini et al. 2013).[24] The relevant SQL coding in order to generate this family size measure can be found in subsection 7.8.

The following table provides descriptive time series analyses on the evolvement of the geographical patent family size measure which are included in those patent documents that are analyzed in this paper. As previously described, these documents refer to the firms' patent applications that can be linked to the Amadeus database based on the matching algorithm provided by Peruzzi et al. (2014). Starting with an overall time series analysis, the table below depicts the annual geographical family size means based on the information contained in Patstat Biblio. It can be seen that the overall mean outcomes of the family size measure are characterized by a decreasing pattern. While the family size mean outcomes amounted to around 8 in the middle of the 1990s, they decreased to around 6 until the mid 2000s and reached its lowest value in 2015 with an overall family size mean of 2.8. Furthermore, also the percentile values, which are depicted in the table below, decrease over time, as for instance the median family outcomes decrease from 6 in 1995 to 2 in 2015 and the third quartile outcomes decrease from 11 in 1995 to 3 in 2015. In order to

Family Size - Summary Statistics
[over Year]

j	N	mean	sd	min	max	p25	p50	p75	p99
1995	32641	8.202	6.839	1	50	4	6	11	33
1996	36402	8.064	6.663	1	52	4	6	11	31
1997	50190	8.234	6.807	1	50	4	6	10	36
1998	62684	7.879	6.586	1	52	4	6	10	32
1999	66200	8.264	7.104	1	53	4	6	10	35
2000	76401	7.836	6.484	1	56	4	6	10	32
2001	80035	7.367	6.157	1	56	4	6	9	33
2002	91570	6.96	5.501	1	52	4	6	8	27
2003	95909	7.213	5.925	1	51	4	6	9	30
2004	107010	6.641	5.422	1	48	3	5	8	28
2005	136319	6.157	4.986	1	48	3	5	8	27
2006	139651	6.228	5.594	1	48	3	5	8	29
2007	146681	5.752	5.051	1	47	2	5	7	26
2008	122310	5.289	4.641	1	45	2	4	7	23
2009	93820	5.518	5.235	1	47	2	4	7	28
2010	92382	4.944	4.578	1	48	2	4	6	24
2011	79577	4.923	4.527	1	41	2	4	6	24
2012	91832	4.381	3.858	1	42	2	4	6	21
2013	76725	4.202	3.703	1	37	2	3	5	20
2014	74995	3.226	3.013	1	37	1	2	4	16
2015	43322	2.871	3.552	1	47	1	2	3	19

Table 4.1

gain a deeper understanding for the underlying factors driving these results, it is important to note that information about the size of a patent family are dependent on the time of publication of the patent offices involved. Due to differences in legal procedures of the offices worldwide as well as due to associated delays, the family size outcomes particularly in the most recent year may suffer from timeliness (Squicciarini et al.

[24]The PCT publication authority (WO) is excluded as it has an international coverage which would inflate the family count by one unit per affected application (see de Rassenfosse et al. (2014)).

2013). As the decreasing pattern can, however, be observed over the whole time frame, more sophisticated analyses are needed. For this purpose, the subsequent set of analyses refers to potential differences of family size values relative to the technological areas of the underlying inventions. As previously described, the classification scheme of patent applications to technology fields is based on the International Patent methodology (Schmoch 2008). The figure below depicts the evolvement of the meaned family size values in the five technological areas from 1995 to 2015. It can be seen, that the shapes of the family size outcomes evolve relatively similar across the different technological sectors. Previous literature, which analyzes patents filed at the EPO, provides numerical outcomes of the family size measure which are consistent with those depicted above, in particular with the Chemistry sector containing higher outcomes compared to the other technological sectors. (Squicciarini et al. 2013). In terms of relative magnitudes, it can be ascertained, that the meaned family size outcomes decrease by around one third from 1995 until 2010 (Chemistry - from 12 to 8; Remaining technological sectors - from 6 to 4), while from 2013 onwards another sharp drop in the family size outcomes, which may be attributable to the above described publication delays of the respective patent offices, can be depicted. These findings indicate that overall decreasing pattern of family size outcomes from above is not driven by a technology-specific development, but rather other, potentially institutional factors. In this context and in line with previous literature, the family size as defined in this paper reports the number of distinct patent offices and not the number of distinct countries per see (de Rassenfosse et al. 2014). As many of the patent applications considered in this paper stem from patent applications filed at the EPO, it is important to note that the number of member states of the European Patent Organisation has increased over time. More precisely, since 1996, in total 21 new countries became member of the EPO, among them countries like Finland, Turkey, the Chech Republic, Hungary, Poland, Croatia and Norway.[25] This rise in member states took place in regular intervals between 1995 and 2015. Consequently, when new countries became members of the EPO and a European patent was filed, no additional patent application was necessarily required as long as the country of interest was included in the priority filing of the EP application.[26] In order to check the validity of this potential channel, the adjacent descriptive figure depicts how the patent family size outcomes differ if all applications that are directly or indirectly linked via priority filings are summarized in an alternative family size measure. The simplified definition of the this measure (which refers to the INPADOC classification contained in Patstat) is that family members

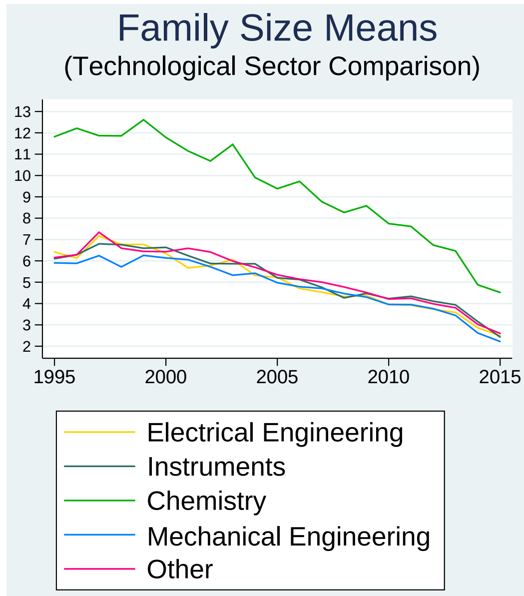


Figure 4.2

[25]A complete overview on EPO member states according to their date of accession can be found here: https://www.epo.org/about-us/foundation/member-states/date.html. *(18. June 2019)*

[26]Note however, that patent filing at a national route is still possible per se, and the EPO membership provides an additional way to seek for patent protection in the jurisdiction of the member country as described above.

relate in some way to the "first" application, which goes beyond filings at different patent offices and is therefore broader than the family size measure presented in this section (EPO 2017a). From the adjacent figure, it can be seen that the time series across the different technological sectors evolve relatively stable from 1995 until 2010, while a drop in the meaned outcomes can only be seen as the current time edge is approached. Besides this, the structural properties of this alternative measure are comparable, particularly regarding the substantially higher outcomes in the Chemistry technology sector. Therefore, this comparative analysis provides support for the consideration that the downward shaped evolvement of the family size measure discussed in this section is attributable to institutional changes regarding the member states of the EPO. The subsequent figure depicts the evolvement of the family size mean outcomes in order to conduct an ANOVA test for the equality of family size means regarding the different technological sectors within the four respective time windows. In context of patent families and technological sectors, previous literature found that patent families from the Chemistry sector carried the highest positive impact on the value of patent rights relative to all other fields of technology (Harhoff et al. 2003). Further related research found that GDP-weighted patent family value consistently rose since 1992 in different technological sectors and during the 2000s more quickly in life science fields such as biotechnology (Kabore and Park 2019). According to the null hypothesis of the ANOVA test, the means of the family size outcomes should be the same in all five technological areas whilst the rejection of the null hypothesis leads to the conclusion that at least two technological sectors have different means. The test is conducted in each of the four time windows and the respective p-values as well as additional confidence intervals for the family size means of each technological sector are depicted based on a 95 percent confidence level in the figure above. Not surprisingly, it can be seen that the p-values of the ANOVA test are zero in all four time windows, indicating that the differences of the family size means between the technological sectors are indeed statistically highly significant, particularly when the Chemistry sector is considered. Besides this, the confidence intervals of the remaining technological sectors indicate that the meaned family size outcomes differ between the other technological sectors as well, while the relative order across the technological sectors changes over time.

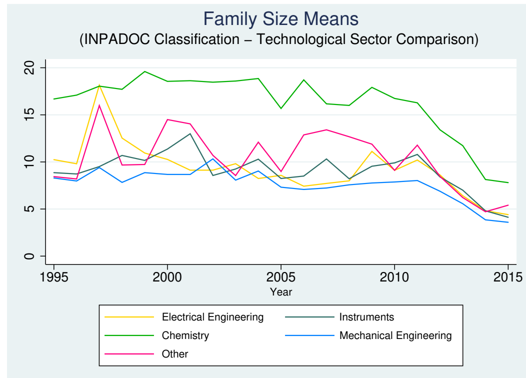


Figure 4.3

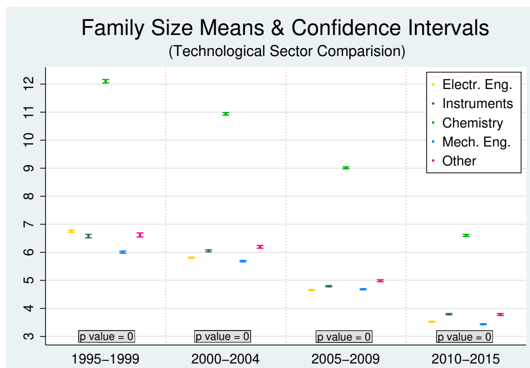


Figure 4.4

These findings are also supported when the overall distributions of the family size outcomes are considered as can be seen from the violin plots below. Chemicals have relatively more mass in their distribution with respect higher family size outcomes compared to the other technological sectors. Additionally, it can be seen that the plots of the remaining technological sectors look quite similar. Besides this, no further differences in the overall distributions of the family size outcomes can be established. Finally, the summary statistics depicted below provide an technology-focused overview on differences regarding the family size outcomes. In line with the above considerations, it can be seen that the overall mean outcomes in the Chemicals sector are substantially higher than those in the other technological sectors and they also contain higher median as well as third quartile values compared to the remaining technological sectors.

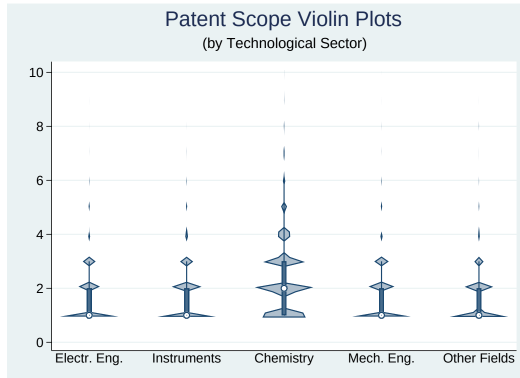


Figure 4.5

Family Size - Summary Statistics
[over Technological Sectors]

Sector	N	mean	sd	cv	min	max	p25	p50	p75
Chem.	452855	9.513	7.656	.805	1	56	4	7	13
E.Eng.	442529	4.941	3.415	.691	1	37	3	4	6
Instr.	208216	5.032	3.783	.752	1	42	3	4	6
M.Eng.	506464	4.742	4.007	.845	1	48	2	4	6
Other	155041	5.221	4.516	.865	1	42	2	4	7

Table 4.2

More detailed time series evolvements of other percentiles from a technological sector perspective can be found in the appendix to this paper in subsections 6.4.1 and 6.4.2 which contain inter alia time series radar plots of meaned, median and percentile family size plots as well as histogram plots over the five different technological sectors.

In the next part, descriptives analyzing the family size outcomes based on patent applications filed by firms with different sizes are provided. The table below depicts the summary statistics for small, medium and large firms.

Family Size - Summary Statistics
[over Firm Size Classifications]

Firms	N	mean	sd	cv	min	max	p25	p50	p75
Large	1127722	5.988	5.511	.92	1	56	2	5	7
Medium	88561	6.504	6.234	.959	1	43	2	5	8
Small	138827	6.818	5.314	.779	1	52	3	6	9

Table 4.3

It is interesting that the overall average family size is the highest for the patent applications of the small firms, followed by the medium firms and lastly the large firms. In order to get a more profound understanding on family size differences across the firm size categories, in a next step the time dimension is also considered. For this purpose, the next figure depicts evolvements of the family size means in four different time windows and a ANOVA test for the equality of family size means in the different firm size categories within four time windows is conducted. It can be seen that the p-values of this test are zero in all four time frames, which indicates that the differences of family size means between the firm size classifications are statistically highly significant. Besides this, it can be seen that large firms had the highest family size outcomes from 1995 until 1999, small firms the highest outcomes from 2000 to 2004 and medium sized firms from 2005 until 2015. According to previous literature, patents held by individuals or small firms are more valuable and value is positively correlated with patent family size. It is argued, that large firms face smaller marginal costs for additional patents, while small firms only patent valuable inventions (Gambardella et al. 2008). These considerations might contribute to explain why small and medium sized firms consistently contain higher family size outcomes from 2000 until 2015. Besides this, literature so far provides rather little insights on the the relation of firm size on patent family size. Therefore, the underlying rationale for the descriptive findings above regarding the differences in family size evolvements provides room for future research. Additional descriptives, which relate to firms' family size outcomes in context of firm size classifications, including distributional plots as well as boxplots, can be found in subsection 6.4.3 in the appendix.

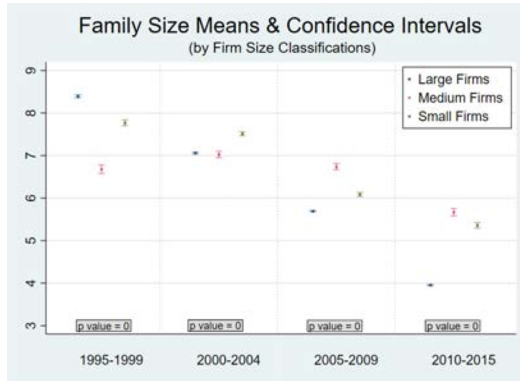


Figure 4.6

The next set of analyses depicts the time series of family size outcomes based on the country classification. The respective summary statistics can be found in the table below. It can be seen that the overall family

Family Size - Summary Statistics
[over Firm Country]

Country	N	mean	sd	cv	min	max	p25	p50	p75
AT	44937	5.806	5.3	.913	1	39	2	4	8
BE	52731	8.854	8.021	.906	1	45	4	6	11
DE	580290	4.742	4.636	.978	1	47	2	4	6
FI	68542	5.749	4.372	.76	1	36	2	5	8
FR	453286	6.286	5.391	.858	1	52	3	5	8
GB	226404	7.955	7.183	.903	1	56	3	6	10
NL	199036	6.713	5.005	.746	1	48	4	5	8
SE	171430	6.066	4.791	.79	1	47	3	5	8

Table 4.4

size means range from 4.7 in Germany to 8.8 in Belgium and, therefore, varies substantially across countries. In order to get a more profound understanding of the cross-country differences, the subsequent figures provide time series evolvements of the meaned family size outcomes along the firm country classification. As can be seen from the p-values from the ANOVA tests which are conducted in each of the four time frames and are contained in the figure below, the differences in average family size outcomes are statistically significant over time across the firm countries. From the figure below, it can also be seen that these differences have become smaller in the time frame from 2010 to 2015 compared to the time frames before.

Recent empirical literature analyzed the development of country-specific measures on the value of patent families in terms of the fraction of family value relative to patent family size (Kabore and Park 2019). It is found that this measure evolves stable until the 2000s for the countries considered and decreases afterwards until 2016. Furthermore, time-persistent differences between countries exist, as for instance Germany was shown to have smaller family value to family size ratios compared to France and the United Kingdom. These time- persistent differences can also be found in the above right figure, as firms from Germany are characterized by systematically lower family size outcomes relative to those from France and Great Britain. According to Kabore and Park (2019), these findings warrant further research, which could also contribute to normative debates on welfare effects of patent protection.[27] In this vein, more sophisticated analyses on these cross-country differences in family size values are conducted in the appendix of this paper. These provide in subsections 6.4.5 to 6.4.7 pairwise correlation analyses of the meaned family size outcomes across the above described firm- and technology-specific dimensions. Furthermore, the related figures in the appendix also contain the numerical magnitudes of the conditional mean outcomes across these dimensions which allow for determining whether substantial level-differences in the family size outcomes exist.

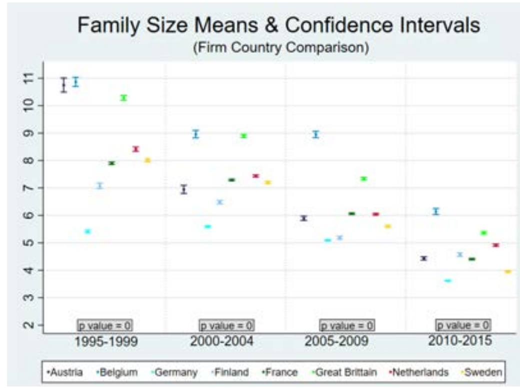


Figure 4.7

3.5 Forward Citations

The following subsection discusses a measure, which captures the citations that a published patent receives from subsequent patents.[28] Based on the considerations from Trajtenberg (1990), this measure is referred to as the patents' *forward* citations and is widely used in literature.[29] Following the rationale that inventors mention prior art in their applications, higher references to particular inventions imply to have a higher relevance for subsequent inventors (Dechezleprêtre et al. 2017). Therefore, the number of received forward citations mirrors the technological importance of a patent for subsequent technologies which was also shown to indicate the economic value of patented inventions. The higher the estimates on the inventions' economic value were, the more the patents were subsequently cited (Harhoff et al. 2003). Numerous empirical studies have verified these findings utilizing different data and methodologies (see for instance Gambardella et al. (2008), Kogan et al. (2017)). Furthermore, it has been shown that forward-citation-weighted patents are strongly correlated with measures of firm value derived from financial market data (Hall et al. 2005, Moser et al. 2015) and that patents, which were renewed to full-term and thereby provided the maximum duration

[27]Another final descriptive, which depicts a histogram of the family size outcomes in different countries, can be found in the appendix of this paper in subsection 6.4.4.

[28]It shall be noted that patent literature cannot be cited before it is published, except for an invention is applied for by the same applicant (OECD 2009).

[29]The references included in patent documents mainly concern the relation towards other patents. Besides this, and to a lesser extent, non-patent literature is also contained as references in patent documents, in particular in terms of related scientific publications (van Raan 2017). Importantly, the references in patents can be included by inventors as well as the responsible patent examiners.

of patent protection, were significantly more cited than patents which expired before their full term was reached (Harhoff et al. 1999). Based on these considerations, forward citations have been utilized as proxies for patent value in analyses of R&D, innovation, and knowledge flows.[30]

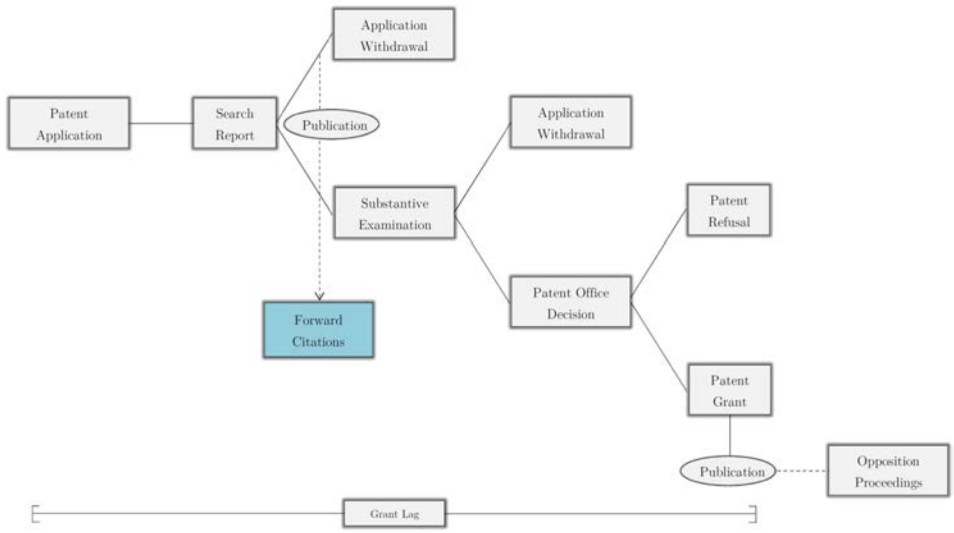


Figure 5.1: Patenting Process Overview

In order to generate the forward citations patent measure, information from the TLS211_Pat_Publn and TLS212_Citations table are utilized. It is important to note that - in order to calculate the forward citations a patent received from all other published patents - one needs to account for the whole universe of published patents from the TLS212_Citations table. Based on the information included in this table, the distinct patent publications which cite a particular patent are counted. In line with previous literature, the forward citations are counted over a period of five years after the publication date (Squicciarini et al. 2013).[31] More detailed specifics regarding the generating process of this forward citations measure can be found in subsection 7.9 of the appendix.[32]

In the subsequent analyses, descriptives on the evolvement of the forward citation outcomes are depicted. Starting with the table below, the summary statistics for the forward citation outcomes are provided. It can be seen that the meaned forward citation values increased between 1995 until 2000 from around 4 to 6 and decreased again to around 3.6 until 2010. Afterwards, a continuous drop in the meaned forward citation outcomes can be depicted until 2015 to around 1.3 Besides this, it can be inferred from the percentile outcomes that while the median values evolved stable until 2013 and dropped afterwards, the third quartile outcomes continuously decreased already from 2010 onwards. Also regarding the maximum outcomes of the forward citation outcomes, a downward pattern can be observed during the most recent years. In order to get some intuition for this descriptive finding, it is important to note that the forward citations variable can only be depicted for those patent applications which were already published. The publication typically

[30] For more detailed insights on related literature, see Falk and Train (2017).

[31] Notably, Squicciarini et al. (2013) compared the distributions of forward forward citations received within a 5-year period after publication with those received within 7 years. The comparison suggested that very little differences existed between these two specifications - not only in aggregate terms, but also when technology-specific patterns were compared.

[32] The command discussed in this section can - in principle - also be utilized in order to generate forward citation outcomes for other time spans.

occurs 18 months after the filing date of the patent (Squicciarini et al. 2013). Consequently, the meaned forward citations outcomes decrease as the current time edge is approached, because more recently publi-

Forward Citations - Summary Statistics
[over Year]

j	N	mean	sd	min	max	p25	p50	p75	p99
1995	8137	3.971	5.416	1	120	1	2	4	26
1996	8735	4.174	6.009	1	128	1	2	5	28
1997	11738	5.25	8.675	1	194	1	3	6	42
1998	15220	5.293	9.356	1	396	1	3	6	43
1999	15866	5.513	9.815	1	341	1	3	6	46
2000	19030	6.064	11.583	1	453	1	3	6	53
2001	19805	5.305	9.507	1	321	1	2	5	42
2002	23440	5.5	10.322	1	529	1	2	6	45
2003	25327	4.751	8.256	1	328	1	2	5	37
2004	32001	5.155	8.277	1	235	1	2	6	39
2005	43765	4.683	6.844	1	204	1	2	5	34
2006	43610	4.306	6.367	1	198	1	2	5	30
2007	47262	4.349	6.449	1	193	1	2	5	30
2008	40299	4.475	6.825	1	190	1	2	5	32
2009	31712	4.211	5.534	1	95	1	2	5	27
2010	30152	3.596	4.607	1	101	1	2	4	23
2011	22469	3.135	3.954	1	96	1	2	4	18
2012	20238	2.363	2.484	1	59	1	2	3	12
2013	9930	1.974	1.838	1	35	1	1	2	10
2014	3632	1.576	1.173	1	21	1	1	2	6
2015	895	1.259	.654	1	9	1	1	1	4

Table 5.1

shed patents have less time to be noted by subsequent inventors and are - in case of applicability - not as likely to become implemented in subsequent related follow-up patents. Additional delays affecting the ability to measure the forward citations may occur as a result of the time lag between the publication date of the cited patent application and the publication date of the referencing search report (Webb et al. 2005).[33] In order to get a more profound understanding about the overall evolvement of the forward citation means - potentially also with respect to the increase between 1995 and 1999 - the subsequent set of analyses refers to potential differences of forward citation values relative to the technological areas of the underlying inventions. The classification scheme of patent applications to technology fields is based on the International Patent methodology (Schmoch 2008). The figure to the right depicts the evolvement of the meaned forward citation values in five technological areas from 1995 to 2015. Interestingly, the shapes of the meaned forward citation time series evolve relatively similar between the Electrical

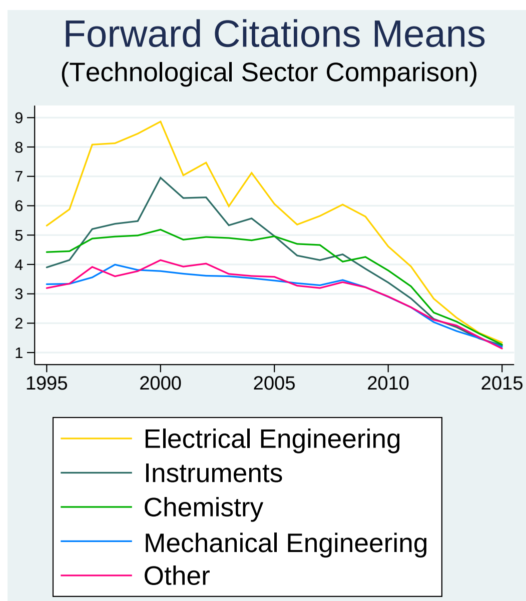


Figure 5.2

[33]Based on these considerations, Squicciarini et al. (2013), who analyzed EPO patent data based on the Patstat 2012 edition, suggested that only patents up to the mid/end of the 2000s should be considered. By analogy, as the current paper relies on the Patstat 2017 edition, the forward citation measures until around 2012 can be considered in a comparative manner.

Engineering and Instruments sectors with their increasing pattern until 2000, while the time series of the other technological sectors are depicted by constant evolvements. In line with the considerations above, the time series of all technological sectors are depicted by decreasing patterns as the current time edge is approached. From these descriptives, it can be inferred that the rising shape of the overall forward citation outcomes between 1995 and 2000 appear to be predominantly driven by the evolvements in the Electrical Engineering as well as the Instruments sector. Furthermore, it is interesting to note that the forward citations referring to patents from the Electrical Engineering sector are persistently higher than those from the other technological sectors while the Mechanical Engineering sector depicts overall the lowest outcomes. This heterogeneity of forward citations between technological sectors can also be depicted from previous literature in related descriptives from a European viewpoint (Squicciarini et al. 2013) as well as from a global perspective (Nagaoka et al. 2010).[34] Furthermore, previous research showed that the propensity to cite other patents differs across technological areas (Hall et al. 2001) which is argued to be determined by the dependence on past technology - with traditional technological fields citing more and being cited less and emerging fields like computers, communications and medical care citing less and being cited more (OECD 2009). These considerations are consistent with the findings from the figure above as patents from the (traditional) Mechanical Engineering sector receive systematically fewer forward citations than patents from the Electrical Engineering, Instruments and Chemistry sector. For a more systematic analysis on differences in forward citations between technological sectors, the adjacent figure depicts the evolvement of the forward citation means in order to conduct an ANOVA test for the equality of these means regarding the different technological sectors within four time windows (1995-1999, 2000-2004, 2005-2009, 2010-2015). According to the null hypothesis of this statistical test, the means of the forward citation outcomes should be the same in all five technological areas whilst the rejection of the null hypothesis leads to the conclusion that at least two technological sectors have different means. Not surprisingly, it can be seen that the p-values of the ANOVA test are zero in all four time windows, indicating that the differences of the forward citation means between the technological sectors are indeed statistically highly significant over time. These findings are also supported when the overall distributions of the forward citation outcomes are considered as can be seen from the adjacent violin plots.

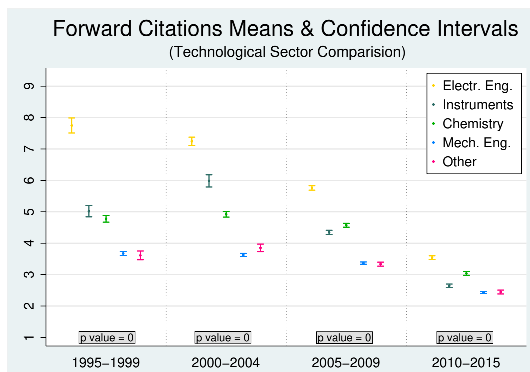


Figure 5.3

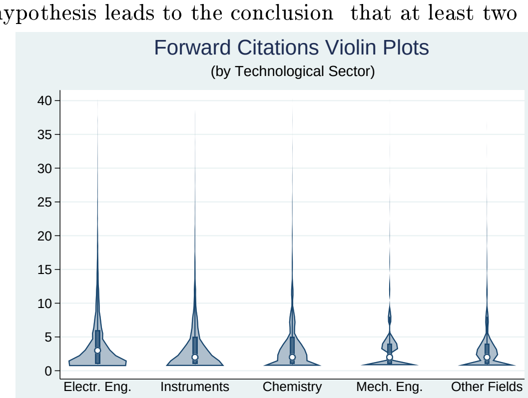


Figure 5.4

[34] One way to control for these differences across technological sectors in empirical analyses is to use relative forward citation counts within the same application year as well as technology field cohort (Nagaoka et al. 2010).

The Electrical Engineering sector has relatively more mass in its distribution with respect to higher forward citation outcomes compared to the other technological sectors. Furthermore, it can be seen that the plots of the remaining technological sectors also contain individual characteristics, particularly when the distribution of the Mechanical Engineering sector is considered. Finally, the summary statistics depicted below provide an technology-focused overview on differences regarding the forward citation outcomes. In line with the above considerations, it can be seen that the overall mean outcomes in the Electrical Engineering sector are substantially higher than those in the other technological sectors, particularly regarding the Mechanical Engineering sector. Besides this, the overall median as well as third quartile values are also higher in the Electrical Engineering sector compared to those of the remaining technological fields. Interestingly, the Mechanical Engineering technological sector contains also a substantially lower maximum forward citation outcome compared to the Instruments, Chemistry and Electrical Engineering sector.

Forward Citations - Summary Statistics
[over Technological Sectors]

Sector	N	mean	sd	cv	min	max	p25	p50	p75
Chem.	103724	4.445	6.6	1.485	1	321	1	2	5
E.Eng.	131123	5.934	10.053	1.694	1	453	1	3	6
Instr.	61240	4.511	7.717	1.711	1	529	1	2	5
M.Eng.	136522	3.289	4.239	1.289	1	190	1	2	4
Other	37837	3.338	4.612	1.382	1	120	1	2	4

Table 5.2

Additional time series evolvements from a technological sector perspective can be found in the appendix to this paper in subsections 6.5.1 and 6.5.2 which contain inter alia time series radar plots of meaned, median and percentile plots of the forward citation measure as well as histogram plots over the five different technological sectors. The next set of descriptives contains analyses on forward citation of the patent applications which were filed by firms with different sizes. From the summary statistics below, it can be seen that the overall average forward citation outcomes are very similar across all firm size classifications.

Forward Citations - Summary Statistics
[over Firm Size Classifications]

Firms	N	mean	sd	cv	min	max	p25	p50	p75
Large	297736	4.496	7.493	1.667	1	529	1	2	5
Medium	22028	4.317	7.892	1.828	1	321	1	2	4
Small	35845	4.66	7.011	1.504	1	204	1	2	5

Table 5.3

Furthermore, also the percentile outcomes are similar across small, medium and large firms, while the maximum forward citation outcomes are by far the highest for large firms and lowest for small firms. In order to compare the forward citation outcomes in a more structural way, the next figure depicts evolvements of the forward citation means in four different time windows and a ANOVA test for the equality of their means in the different firm size categories within four time windows is conducted.[35] It

[35]The utilized one-way ANOVA is a statistical test to compare the groups given that the outcome variable is

can be seen that the p-values of this test are zero in three time frames, which indicates that the differences of forward citation means between the firm size classifications are statistically highly significant between 1995 until 2009 and statistically insignificant between 2010 until 2015. Besides this, it can be seen that the relative order between the firm size classifications changes over time and the confidence intervals contain overlaps also in the time frame between 1995 and 2009. These results appear particularly interesting as it might have been expected that patents from big players received more public awareness which potentially resulted in higher amounts of received forward citations. However, as patents from small firms do not contain systematically fewer forward citations than medium and large firms over time, this rationale can not be supported by the descriptive evidence presented in this paper. Besides this. literature so far provides surprisingly little structural insights on this relation and thereby contains substantial room for future research. More descriptives, which relate to firms' forward citation outcomes in context of firm size classifications, including distributional plots as well as boxplots, can be found in subsection 6.5.3 in the appendix.

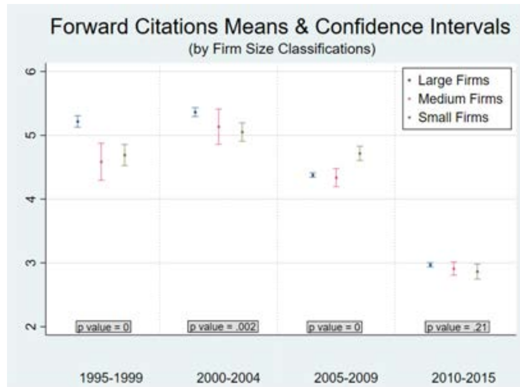


Figure 5.5

The next set of analyses depicts the time series of forward citation outcomes based on the country classification. The respective summary statistics can be found in the table below. It can be seen that the overall forward citation means range from 3.7 in Germany to 7.1 in n Finland and, therefore, vary substantially

Forward Citations - Summary Statistics
[over Firm Country]

Country	N	mean	sd	cv	min	max	p25	p50	p75
AT	10160	3.399	4.341	1.277	1	90	1	2	4
BE	12429	4.229	5.482	1.296	1	152	1	2	5
DE	171198	3.68	5.571	1.514	1	529	1	2	4
FI	16508	7.066	12.799	1.811	1	335	1	3	7
FR	105425	4.013	6.048	1.507	1	196	1	2	4
GB	60341	4.738	7.091	1.496	1	226	1	2	5
NL	51735	5.183	8.509	1.642	1	328	1	3	6
SE	45467	6.322	11.086	1.754	1	453	1	3	7

Table 5.4

across countries. In order to get a more profound understanding of the cross-country differences, the subsequent figures provide time series evolvements of the meaned forward citation outcomes along the firm country classification. As can be seen from the figures below, there are time persistent and considerably different evolvements of the forward citation outcomes across countries. For instance, Finland is characterized by big fluctuations in forward citation outcomes over time, while other countries tend to have rather smooth evolvements in their forward citations over time. These cross country differences in forward

continuous and that there are more than two groups (Kao and Green 2008). According to the null hypothesis, the means of the patent scope outcomes should be the same in all firm size classifications whilst the rejection of the null hypothesis leads to the conclusion that at least two firm size classifications have different means.

citation outcomes were also documented by previous literature from a European perspective (Squicciarini et al. 2013). Interestingly, from the figures below it can be seen that the Scandinavian countries Finland and Sweden appear to be the time persistent top scoring countries with respect to their meaned forward citation outcomes. In this context, it is important to note that patent citation data are checked and edited in the course of patent examinations at the EPO. The EPO examiner is required to provide the most relevant prior art references in the search report and, finally, the patent application document (Nagaoka et al. 2010). The presence of this institutional control mechanism ensures that the scope of patent protection which is claimed by subsequent patentees is correctly specified (OECD 2009). Furthermore, this institutional structure implies that the above described forward citation differences across the countries considered are unlikely to be driven by cross-country differences regarding the inclusion of previous knowledge in subsequent patents if the EPO was considered as the patent filing institution. Subsection 6.5.6 of the paper contains further descriptives as to whether these cross-country differences are potentially related to associated differences across the technological sectors in which the patent applications were filed in different countries.[36] In summary, the underlying reasons for the established descriptive findings provide room for further and more sophisticated analyses. More research might provide explanations to the depicted descriptive findings regarding the forward citation outcomes in order to get a better understanding of the underlying drivers of the time-persistent differences of the forward citation outcomes across countries.

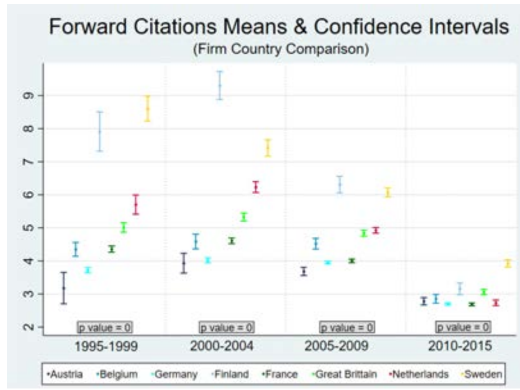


Figure 5.6

3.6 Backward Citations

The next subsection discusses another citation-based measure, which provides information on the technological background as well as the prior knowledge based on which new patent applications are filed. While the degree to which patented inventions are linked to basic science is difficult to determine, patent applications contain lists of references to earlier patents as well as to non-patent literature (NPL) such as scientific papers, which set the legal boundaries of the claimed novelty of the patent and its inventive activity (Guellec et al. 2012, Cassiman et al. 2008). These references are added either by the applicant or the patent examiner in the search report in order to reflect the prior art based on which new inventions are built upon and in order to ensure that all previous relevant literature and patents are included (Criscuolo and Verspagen 2008, OECD 2011).[37]

[36] Besides this, subsections 6.5.5 and 6.5.7 amongst others contain the respective descriptive analyses regarding the way the conditional forward citation means are correlated across the firm countries over the three firm size classificaitons.

[37] Citations of patents in EPO patents are contained in the search report, which constitutes a separate document attached to the patent (Criscuolo and Verspagen 2008). In EPO patents, about 10% of the citations are added by the inventor while at the USPTO this proportion increases to 60% which is explained by the duty of candor in the US patent system (Pillu 2009). It should be noted that under Rule 27(1)(b) of the European Patent Convention

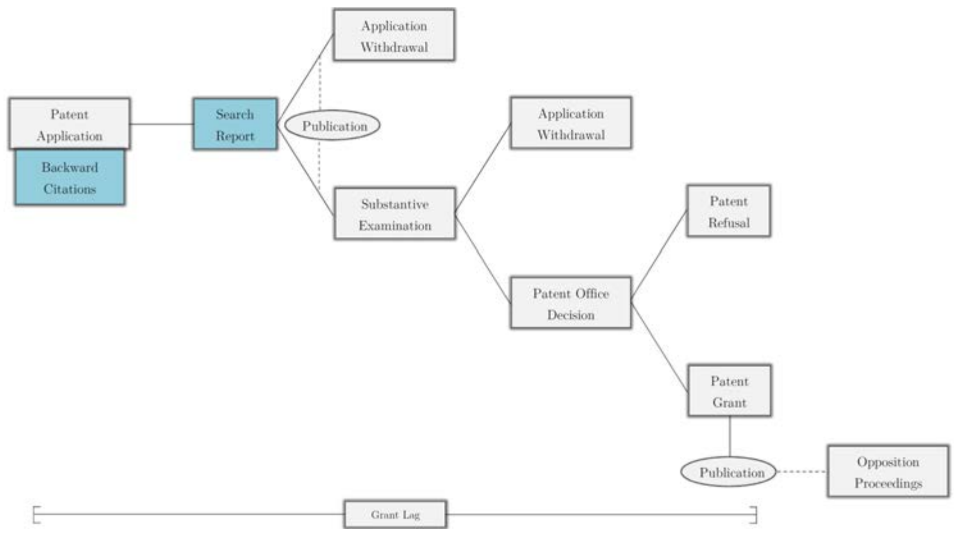


Figure 6.1: Patenting Process Overview

Patent citations have been used by previous literature as indicators of technological flows and knowledge spillovers. It is argued that when one patent cites another patent, this constitutes an indication for the usefulness of the cited patent for the development of new knowledge (Criscuolo and Verspagen 2008). For a set of French EPO patents, Duguet and MacGarvie (2005) found that the included backward citations are positively and significantly correlated with learning through R&D collaboration as well as with mergers and acquisitions. Furthermore, Harhoff et al. (2003) found that the number of backward citations is positively correlated with the value of a patent. Lanjouw and Schankerman (2001b), on the other hand, argued that large numbers of backward citations may also be a signal of the innovation to be of rather incremental nature in established technology areas and therefore make backward citations a rather weak measure for the inventory quality of patent applications because firm value effects of incremental innovations might be considered to be rather weak. This argument is attenuated by the findings from van Wartburg et al. (2005) who found a positive and significant correlation between a measure of patents' backward citations and expert ratings regarding their technological value added which implied that patents with higher technological value build on more references. Besides this, Harhoff et al. (2003) provide anecdotal evidence, according to which several patent lawyers and examiners pointed out that patent applications that seek to protect inventions of a broad scope may induce the patent examiners to lay out the patent claims by inserting more references to the relevant literature. Finally, Liu et al. (2011) find a high positive correlation between the number backward citations and the probability of the patent being able to stand up in court.

In order to generate the backward citation measure, information from the TLS212_Citation table are utilized. The backward citations measure which is discussed in this subsection covers references from prior

there is no obligation to provide a list of references describing the state of the art which are considered relevant to the patentability of the invention, i.e. there is no so-called duty of candor (Criscuolo and Verspagen 2008). Nevertheless, it is argued that inventors still will include all prior art in their patent application. Inter alia, applicants might provide a very detailed documentation in order to avoid future objections from third parties and, following this, strengthen the bargaining power in courts (Akers 2000, Criscuolo and Verspagen 2008). Furthermore, the examination authority may add additional relevant patents as well as remove irrelevant patents if they were deemed not to be relevant for the respective patent (Alcácer and Gittelman 2006). Further details regarding legal particularities between the EPO and the USPTO that result in different citation outcomes can be found in Criscuolo and Verspagen (2008).

patents as well as from non-patent literature.[38] More specifics regarding the generating process can be found in subsection 7.10 of the appendix. In the subsequent analyses, descriptives on the evolvement of the backward citation outcomes of those patents that can be linked to the Amadeus database based on the matching algorithm provided by Peruzzi et al. (2014) are depicted. The table below shows annual summary statistics for the backward citation outcomes based on the information contained in Patstat Biblio.

Backward Citations - Summary Statistics
[over Year]

j	N	mean	sd	min	max	p25	p50	p75	p99
1995	15097	6.56	7.255	1	146	3	5	8	34
1996	16196	6.299	6.718	1	195	3	5	7	28
1997	20812	6.585	6.914	1	156	3	5	8	32
1998	26393	6.564	8.938	1	225	3	5	7	33
1999	28084	7.146	9.96	1	280	3	5	8	43
2000	33095	7.382	11.067	1	385	3	5	8	46
2001	35696	6.877	9.734	1	390	3	5	7	38
2002	41886	6.993	9.65	1	266	3	5	7	44
2003	43794	7.043	10.208	1	230	3	5	7	46
2004	53204	7.825	12.3	1	509	3	5	8	58
2005	69033	8.069	12.908	1	451	3	5	8	56
2006	73529	8.071	14.124	1	637	3	5	8	67
2007	81396	7.956	13.124	1	551	3	5	8	60
2008	73249	8.099	12.97	1	436	3	5	8	62
2009	57912	8.231	13.112	1	281	3	5	8	63
2010	59927	8.53	14.614	1	672	3	5	8	71
2011	52944	8.921	19.844	1	1003	3	5	9	72
2012	60967	7.729	13.111	1	630	3	5	8	59
2013	49570	7.635	14.925	1	572	3	5	7	60
2014	50932	6.473	10.629	1	808	3	5	7	43
2015	33734	6.463	10.728	1	386	3	5	7	43

Table 6.1

It can be seen that the meaned backward citation values increased between 1995 until 2011 from around 6.3 to 8.9 and decreased afterwards again to around 6.4 in 2015 as can also be seen in the adjacent figure. Furthermore, from the percentile outcomes in the table above it becomes evident that the median values amount to 5 within the whole time range and also the first and third quartile outcomes remain constant during the whole time frame considered. From these considerations and in line with findings from previous literature, it can be inferred that the backward citation outcomes do not suffer much from truncation, since backward citations are typically included within the first two years after application in the patent document by the corresponding patent examining authority (Squicciarini et al. 2013). As the current paper relies on the Patstat 2017 edition, the backward citation outcomes until around 2015 can be considered as reliable. Besides this, as can be seen from the 99th percentile values and even more by

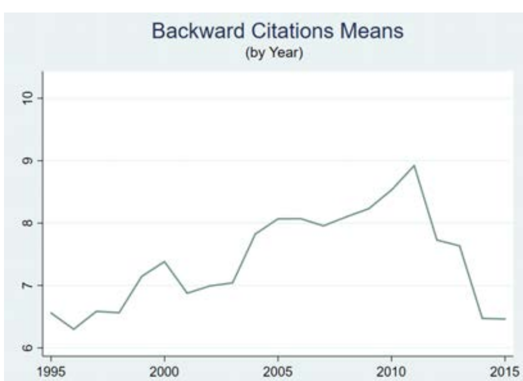


Figure 6.2

[38]Previous analyses showed that citations to non-patent literature are highly dependent on the technological sector considered. While on average the share of NPL citations amounts to around 20%, in biotechnology the share amounts to around 50%, while in chemical engineering the share amounted to less than 10% (OECD 2011). In order to get an overall picture regarding the dependence of a patented invention to previous knowledge, the patent measure discussed covers references to both, patent and non-patent literature.

the maximum outcomes per year the backward citation distributions are depicted by long right tails over time.

In order to get a more profound understanding about the overall evolvement of the backward citation means - potentially also with respect to the increase between 1995 until 2011 - the subsequent set of analyses refers to potential differences of backward citation values relative to the technological areas of the underlying inventions. The classification scheme of patent applications to technology fields is based on the International Patent methodology (Schmoch 2008). The figure below depicts the evolvement of the meaned backward citation values in five technological areas from 1995 to 2015. It becomes apparent that a substantial increase in the backward citations took place within the Chemistry sector between 1995 until 2011 in which the meaned outcomes basically doubled from 8 to 16. The development within the other technological sectors, on the other hand, provide rather constant evolvements between 1995 and 2011 while all technological sectors are characterized by decreases in their backward citation outcomes between 2011 and 2015. Besides these developments, there appear to be time-persistent level differences between the technological sectors. Related literature argues that industrial variations in disclosures of prior art may be rooted in differences in applicants' incentives (Jaffe and de Rassenfosse 2017). It was shown in a theoretical setup that firms search more for prior art when investments in R&D and patenting costs are higher (Atal and Bar 2010). In the same vein, it was also shown empirically that applicants are more involved in the search for prior art in technological fields such as chemistry and drugs in which individual patents were important for appropriating returns from R&D, while they are less involved in industries in which firms build up patent portfolios for other strategic reasons such as in mechanical and electrical engineering (Sampat 2010). While these previous findings contribute to explain the depicted differences in backward citations between the technological sectors, the strong increase in backward citations in the chemistry sector remains a remarkable descriptive finding.[39]

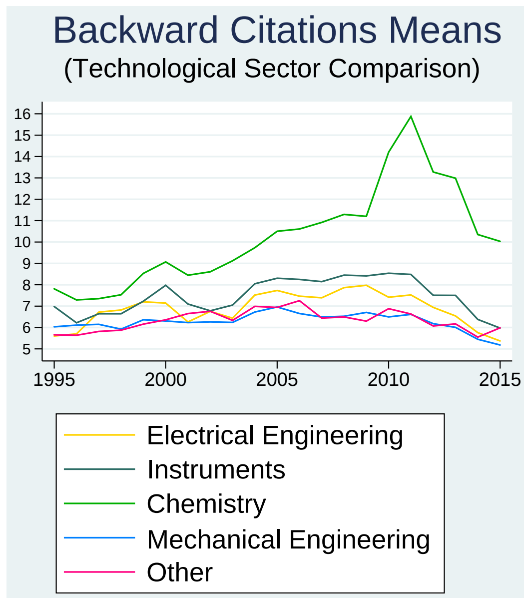


Figure 6.3

For a more systematic comparison on the differences in backward citations between the technological sectors within this firm context, the figure below depicts the evolvement of the backward citation means in order to conduct an ANOVA test for the equality of these means regarding the different technological sectors within the four time windows. Not surprisingly, it can be seen that the p-values of the ANOVA test are zero in all four time windows, indicating that the differences of the backward citation means between the technological sectors are indeed statistically highly significant over time. Also regarding the other

[39]Subsequent analyses might analyze whether these particular findings stem from the sample dataset of this paper or whether they can be replicated with other subsets of te Patstat database (for instance patent filings of individuals) as well.

technological sectors, the confidence intervals indicate that the meaned outcomes are indeed systematically

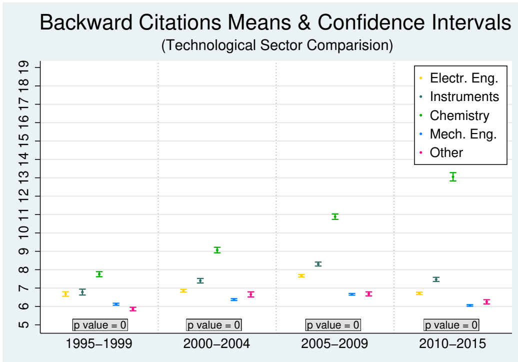


Figure 6.4

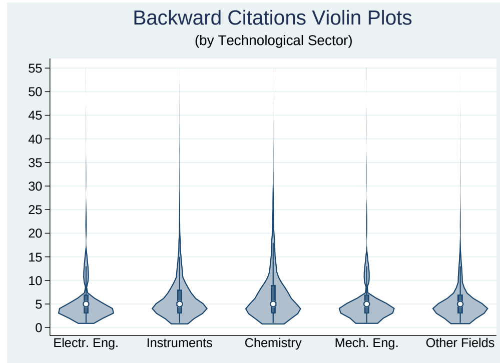


Figure 6.5

different. These findings are also supported when the overall distributions of the backward citation outcomes are considered as can be seen from the violin plots above. The Chemistry sector has relatively more mass in its distribution with respect to higher backward citation outcomes compared to the other technological sectors. Besides this, it can be seen that the plots of the Electrical as well as Mechanical Engineering sector are depicted by similar distributional violin plot shapes, while the shapes of the Instruments, Chemistry and Other Fields sectors also appear relatively similar. Finally, the summary statistics depicted below provide an technology-focused overview on differences regarding the backward citation outcomes. In line with the findings and considerations from above, it can be seen that the overall mean outcomes in the Chemistry sector are substantially higher than those in other technological sectors. Besides this, the

Backward Citations - Summary Statistics
[over Technological Sectors]

Sector	N	mean	sd	cv	min	max	p25	p50	p75
Chem.	207115	10.693	21.388	2	1	1003	3	6	10
E.Eng.	260954	7.093	9.854	1.389	1	242	3	5	8
Instr.	124233	7.711	11.127	1.443	1	254	3	5	8
M.Eng.	297386	6.332	6.845	1.081	1	222	3	5	7
Other	84385	6.444	9.094	1.411	1	212	3	5	7

Table 6.2

overall median as well as third quartile values are also higher in the Chemistry sector compared to those of the remaining technological fields which depict very similar outcomes. Interestingly, the maximum backward citation outcomes in all technological sectors apart from the Chemistry sector are comparable in size and consistent with the numerical backward citation outcomes from recent literature (Kuhn et al. 2017). Additional time series evolvements from a technological sector perspective can be found in the appendix to this paper in subsections 6.6.1 and 6.6.2 which contain inter alia time series radar plots of meaned, median and percentile plots of the backward citation measure as well as histogram plots over the five different technological sectors.

The next set of descriptives contains analyses on backward citations of the patent applications which were filed by firms with different sizes. From the summary statistics below, it can be seen that the overall average backward citation outcomes are highest for small firms and lowest for large firms. Besides this, the percentile outcomes are quite similar across the firm-size categories. The maximum backward citation

Backward Citations - Summary Statistics
[over Firm Size Classifications]

Firms	N	mean	sd	cv	min	max	p25	p50	p75
Large	616874	7.333	11.862	1.618	1	1003	3	5	8
Medium	47596	8.486	16.854	1.986	1	436	3	5	8
Small	71610	8.939	15.348	1.717	1	393	4	5	9

Table 6.3

outcomes are, however, the highest for large firms, followed by those of medium and small firms. For a more structural comparison, the next figure depicts evolvements of the backward citation outcomes in four four different time windows and a ANOVA test for the equality of their means in the different firm size categories within four time windows is conducted. It can be seen that the p-values of this test are zero all four time frames, which indicates that the differences of forward citation means between the firm size classifications are statistically highly significant. Besides this, it can be seen that the relative order between the firm size classifications remains constant over time with small firms containing systematically the highest and large firms the lowest backward citation outcomes over time. Some parts of previous literature suggest that organizational characteristics provide differential incentives to firms regarding their disclosure behavior of prior art. It is argued that larger firms are likely to have more resources to invest in lawyers and patent searchers in order to conduct prior art searches and, therefore, have a greater shares of prior art in their patent documents relative to the prior art added by the patent examiners (Mossinghof 1999). On the other hand, it is argued that small firms might have more incentives to license patents rather than commercializing them in-house (Arora et al. 2004) and, therefore, be ex ante more engaged to invest in the search for prior art than their large counterparts (Alcácer et al. 2009).[40] In this context, it should be borne in mind that the patent examining authorities also have substantial impact on the total number of backward citations included in patent documents (Pillu 2009). Nevertheless, the above considerations regarding firms' incentives to provide prior art in their patent documents provide a potential channel in order to explain the above described differences in backward citations across small, medium and large firms. More descriptives, which relate to firms' backward citation outcomes in context of firm size classifications, including distributional plots as well as boxplots, can be found in subsection 6.6.3 in the appendix.

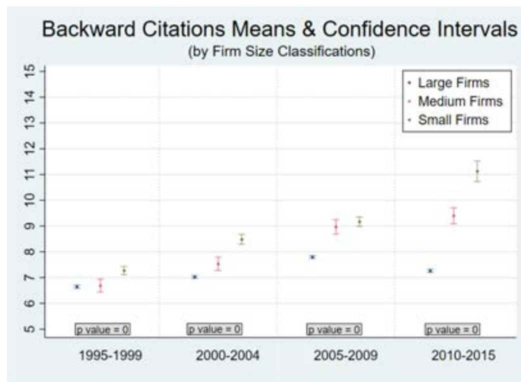


Figure 6.6

In the subsequent set of analyses, the time series of backward citation outcomes based on the country classification is depicted. The respective summary statistics can be found in the table below. From this

[40]Further related literature regarding firms and their willingness to disclose prior knowledge can be found for instance in Steensma et al. (2015) and Corsino et al. (2019)

table, it can be seen that the backward citation means range from about 6.9 in Austria to 9.7 in Belgium.

Backward Citations - Summary Statistics
[over Firm Country]

Country	N	mean	sd	cv	min	max	p25	p50	p75
AT	23709	6.93	9.579	1.382	1	200	3	5	8
BE	24832	9.764	18.958	1.942	1	390	4	5	9
DE	340854	7.429	12.636	1.701	1	672	3	5	8
FI	28625	7.952	11.258	1.416	1	277	3	5	8
FR	267340	7.015	11.524	1.643	1	1003	3	5	7
GB	118946	8.837	15.881	1.797	1	808	3	5	8
NL	89816	7.895	11.669	1.478	1	509	3	5	8
SE	83328	7.995	11.903	1.489	1	222	3	5	8

Table 6.4

Therefore, some variation in the overall backward citation means can be observed across the firm countries considered. The subsequent figures provide more detailed evolvements of the backward citation outcomes across the firm countries, as the time dimension is additionally taken into account. It is interesting to note

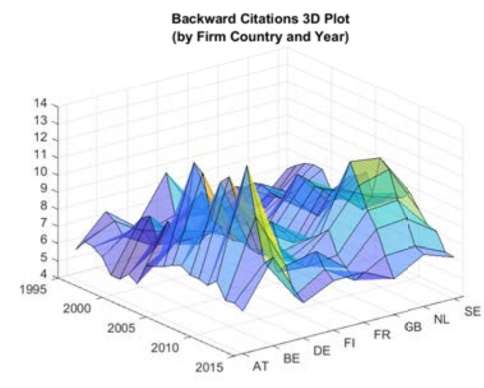


Figure 6.7

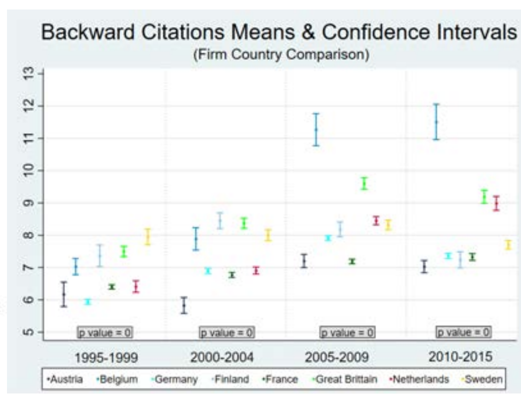


Figure 6.8

that the evolvements of backward citations means between 1995 until 2004 were aligned relatively close to each other across the different firm countries, whilst between 2005 until 2015 some divergence took place - in particular when Belgium, Great Britain and the Netherlands are considered. Some indications for the underlying reasons of these cross country differences can be found in related literature. While many of the patent applications considered are filed at the EPO, another fraction of the patent applications are filed within the United States at the USPTO or at other national patent offices. Depending on the destination countries of the patent applications, country-specific patent practices might affect the applicants awareness and ability to include prior art in their application, because in most foreign countries the applicants do not face a duty of candor as in the United States (Alcácer et al. 2009). Following these institutional differences between different patent filing countries, it is argued that the prior art searches of the applicants in Europe are more selective than in the United States (Michel and Bettels 2001). In this vein, it was for instance recently shown that US patents cited on average more patents than German patents (Fischer and Ringler 2015). Building on these descriptive findings, the appendix contains further descriptive figures and tables that provide analyses on the pairwise correlations of the meaned backward citations outcomes across the above-discussed firm- and technology-specific dimensions.

4 Patent Measures from Patstat Legal Status

In a next step, further patent measures which are derived from the Patstat Legal Status database are introduced. According to Chapter 5.23 of the EPO Biblio and Legal Data Catalog, the TLS231 Inpadoc Legal Event table contains information on legal events which occurred during the life of a patent, either before or after grant and are depicted as textual legal event codes. In order to translate these legal event codes into numerical representations, additional information which were provided by the EPO are utilized (EPO 2018). Based on these information, the patent measures referring to legal events are generated as indicator variables and indicate whether a patent document was affected by a legal event, for instance regarding its oppositions or renewals. Further details on the underlying coding can be found in the appendix of this paper in subsection 7.11.

4.1 Oppositions

The first measure which is based on the information from the Patstat Legal Status Database relates to the possibility of third parties to oppose granted patents which they deem to be invalid.

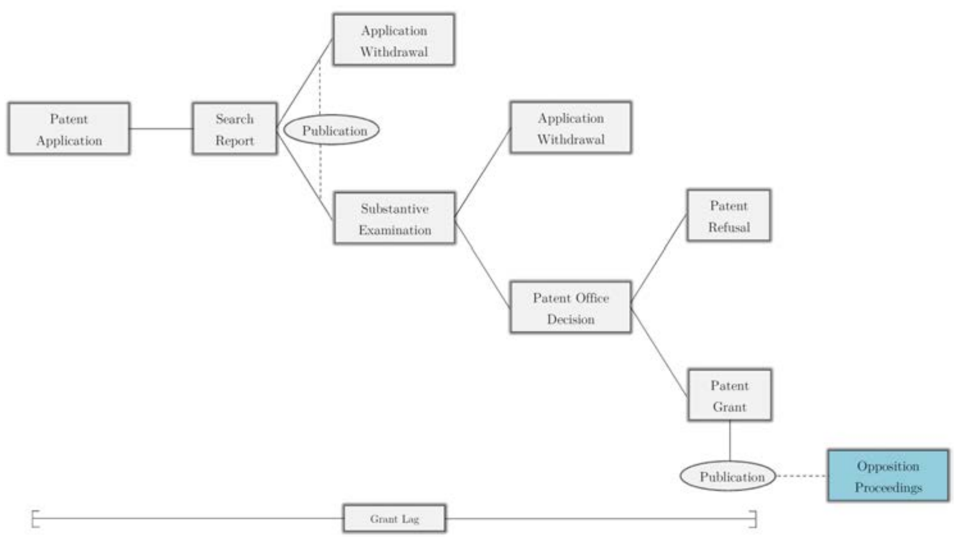


Figure 7.1: Patenting Process Overview

Patent oppositions indicate that the applicant as well as the opposing party are willing to accept additional costs in order to protect their property rights (Lanjouw and Schankerman 2001b, Dechezleprêtre et al. 2017). For instance, the costs of opposing a patent at the EPO have been estimated to range from 6.000 to 50.000 Euro (Harhoff et al. 2016). Previous empirical literature has shown that more valuable patents are more likely to be opposed than less valuable ones (Harhoff et al. 2003). Therefore, the opposition procedure may serve as an information revelation mechanism which selects valuable patents based on third party information (Harhoff et al. 2016). On average only 8% of all EPO patents - likely those with the highest value - are opposed (Harhoff et al. 2003, Harhoff and Reitzig 2004).[41] However, it was also shown

[41]The higher opposition rates observed in this paper arguably stem from the analyzed sample which is restricted to a subset of patents which stem from inventive European firms. Potentially, the patents of these inventive firms are more likely to be opposed than patents filed by other agents such as individual inventors, whose inventions arguably have a smaller reach and therefore are less likely to be opposed.

by previous literature that the opposition rates and outcomes for EPO patents vary and leading companies face oppositions of their patents far more often than on average which go beyond 20% (van der Drift 1988).[42] From an US perspective, parties who aim at challenging a US patent after it has been issued can request re-examination of the patent by the USPTO, while the respective re-examination rate is much lower than the opposition rate at the EPO (OECD 2009).

The outcomes regarding the patent opposition variable are either 1 or 0, indicating whether a particular patent application was opposed (=1) or not (=0). Further details regarding the respective coding in order to obtain information on the patent oppositoins can be found in the appendix of this paper in subsection 7.11. Therefore, the meaned outcomes of the opposition values can be interpreted as percentage shares of those patent applications which were opposed.

The subsequent analyses depict selected descriptives on the evolvement of the opposition outcomes of those patents that can be linked to the Amadeus database based on the matching algorithm provided by Peruzzi et al. (2014).[43] In a first step, the evolvement of the patent opposition shares in different technological sectors over time are provided. From the adjacent figure, it can be seen that the time series of the meaned opposition outcomes are characterized by a decreasing pattern in all technological sectors in the four time windows considered. This decreasing pattern of opposition rates was also observed by previous literature in a different time window (Harhoff et al. 2016) and may be partly attributable to specific truncation issues, even though oppositions or re-examination proceedings can only be filed within 6 to 9 months after the publication of the patent grant (Jones 2018). As described in section 4.1 of this paper, the granting procedure of patent application takes considerable time and, therefore, contributes to explain the decreasing pattern of the patent oppositions rates. In this vein, the drop in opposition rates between 2010 and 2015 is particularly related to the patent granting procedure, as many of the filed patents in this time frame are still under examination and, therefore, barred from being opposed by third parties. Furthermore, it is interesting to note that there are systematical differences in opposition rates between the technological sectors. In particular, Electrical Engineering is depicted by the lowest opposition rates between 2000 and 2015 which is in line with the findings from Harhoff et al. (2016). On the other hand, the descriptive findings from above indicate that the patents from the Mechanical Engineering sector tend to have the highest opposition rates, while the opposition rates of the Chemistry and Instruments sector lie in the middle. In order to evaluate this notion, the above figure contains an ANOVA test for the equality of the opposition means regarding the different technological sectors within the four time windows considered. According to the null hypothesis of this statistical test, the means of

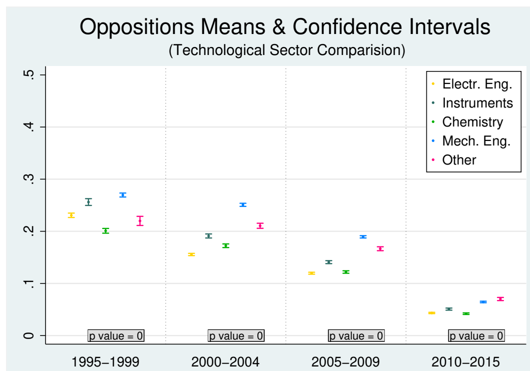


Figure 7.2

[42] Notably, personal interviews of Harhoff et al. (2003) with patent examiners suggested that similar differences also characterized the opposition process at the German Patent Office.

[43] As the opposition variable is generated as an indicator variables, no summary statistic tables need to be provided in this subsection.

the opposition outcomes should be the same in all five technological areas whilst the rejection of the null hypothesis leads to the conclusion that at least two technological sectors have different means. It can be seen that the p-values of the ANOVA test are zero in all four time windows, indicating that the differences of the opposition rate outcomes between the technological sectors are statistically highly significant over time. Besides this, the opposition rates of the patent applications considered in this paper appear to be very high in comparison to the above-described rates from previous literature. These differences may be partly attributed to the fact that the opposition rates generated in this paper are restricted to the patent applications filed by large corporate European inventors. Potentially, the patents of these inventive firms are more likely to be opposed than patents filed by other agents such as individual inventors, whose inventions arguably have a smaller reach and therefore are less likely to be opposed. In line with this, leading firms may face oppositions more often relative to other patent filing groups such as individuals or other public scientific institutions which could additionally contribute to explain the high opposition rates from above (Harhoff et al. 2003, van der Drift 1988).

The next set of descriptives contains analyses on opposition outcomes of the patent applications which were filed by firms with different sizes. The figure below depicts the evolvements of the opposition means in the four different time windows and a ANOVA test for the equality of their means in the different firm size categories within four time windows is conducted.[44] It can be seen that the p-values of this test are zero in all four time frames, which indicates that the differences of the opposition rates across the firm size classifications are statistically highly significant between 1995 and 2015. The opposition shares are systematically higher for large and medium firms and compared to those of the small firms. These results are in line with considerations from previous literature which point out that opposition rates of big and technologically leading firms have opposition rates exceeding 20% (Harhoff et al. 2016, van der Drift 1988). A final set of analyses depicts the time series of opposition outcomes based on the firm country classification. For this purpose, the adjacent figure provides the time series evolvements of the meaned opposition rate outcomes in the four time windows. Interestingly, it can be seen that there are time persistent differences in patent opposition rates across firms from different countries. For instance, patents from German firms systematically contain the highest opposition rates between 1995

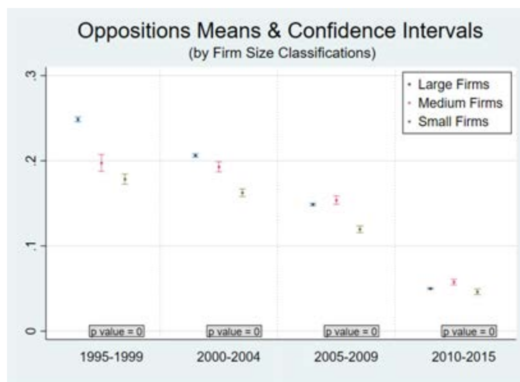


Figure 7.3

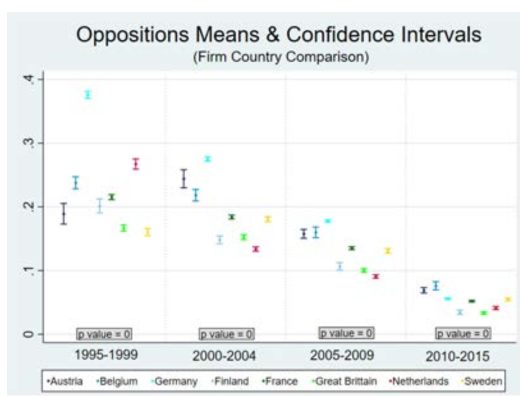


Figure 7.4

[44]The utilized one-way ANOVA is a statistical test to compare the groups given that the outcome variable is continuous and that there are more than two groups (Kao and Green 2008).

until 2009, while the opposition rates for patents from British firms appear to be relatively low. These differences are also highly statistically significant based on analogous ANOVA tests. Further descriptive figures and tables are contained in the appendix, which provide pairwise correlations of the meaned opposition rate outcomes across the above described firm- and technology-specific dimensions. Subsection 6.7.1 provides insights as to whether and how the opposition rate outcomes of the firms' patents are correlated across the firm countries over the three firm size classifications. Therefore, conditional means on the opposition rate durations are generated for each firm country and firm size combination. Based on these conditional means, the correlation coefficients are calculated which contain comparative insights regarding the opposition rate evolvements across the firm countries and firm size combinations. Besides this, the related figures in the appendix also contain the numerical magnitudes of the conditional mean outcomes across these dimensions which allow for determining whether substantial level-differences in the opposition rates. Subsection 6.7.2 contains the respective descriptive analyses regarding the way the conditional opposition rates of the patent applications filed by firms from different countries are correlated across the technological sectors in which these patents were filed in. Finally, subsection 6.7.3 of the appendix provides deeper insights with respect to the evolvements of the opposition rates as well as the correlation coefficients across firms with different sizes and the technological sectors of the corresponding patent filings.

4.2 Renewals

The next measure which utilizes information from the Patstat Legal Status Database analyzes the rate of renewals of those patents which have previously been granted by the relevant patent authorities. Data on patent renewals have been widely used by literature in order to make inferences on the value of patented inventions (OECD 2009).

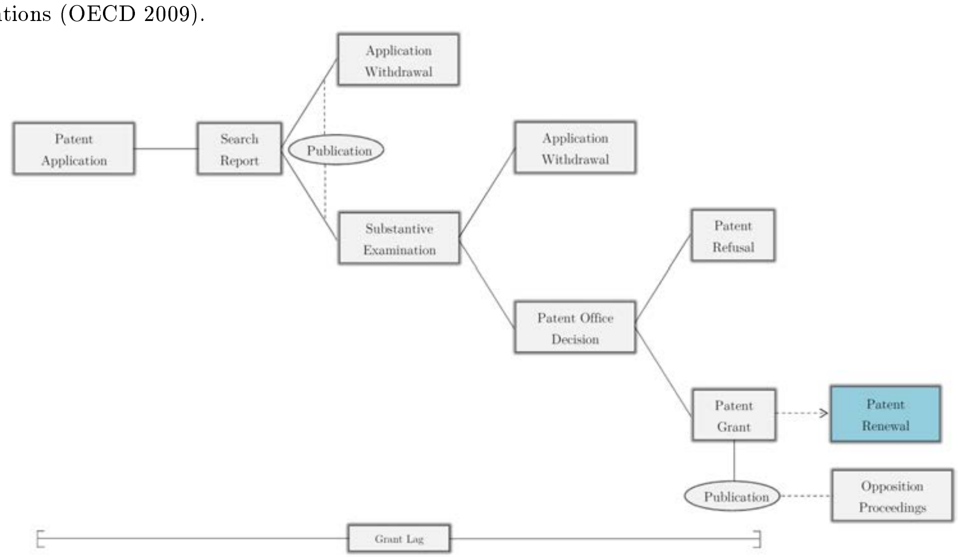


Figure 8.1: Patenting Process Overview

In all major jurisdictions, the patent grant has to be maintained by regular renewals which involve the payment of corresponding fees (Christie and Rotstein 2008). In context of patents filed at the EPO, it is important to note that under Articale 2(2) of the European Patent Convention, every European patent is subject to the same conditions in each of the states for which it is granted as a national patent granted by the respective state. In the European setup, the national patents can be maintained in the contracting states for different periods, such that patentees have to choose whether to renew their national patents or not.[45] For patents filed at the Japanese or Korean patent offices, the annual fees are paid in one tranche for the first three years and on an annual fee basis for subsequent years. For patents filed in the United States at the USPTO, maintenance fees are not collected on annual basis, but after 3.5, 7.5 and 11.5 years after the grant date (IP5-Report 2017). It is argued in literature that patent renewals are useful in order to estimate the true value of the patent right itself (Hall and Harhoff (2012)). The underlying rationale is that - given an assignee pays renewal fees - this implies that he expects to earn at least the cost of the fee through the use of the technology in production, licensing and commercialization of the patent (Dechezleprêtre et al. 2017). This argument becomes even stronger as renewal fees typically increase over time (OECD 2009). Based on these considerations, many researchers have utilized information on patent renewals in their analyses (Pakes and Schankerman 1984, van Pottelsberghe de la Potterie and van Zeebroeck 2008, Hegde and Sampat 2009). Renewal fees are rather low. Therefore, they are rather unable to give insights about the value distribution for the tails, i.e. regarding where the highest-value patents lie (Hall and Harhoff 2012).[46] Based on chapter 6.6 of the 2017 EPO Biblio and Legal Data Catalog, the variable *fee_ renewal_ year* captures the count year of annual renewal fee payments for a European patent. From these information, an indicator variable is generated which captures whether the renewal fees were payed for a patent (=1) in a particular year or not (=0). The meaned outcomes of the renewal values can, therefore, be interpreted as percentage shares of those granted patents which were renewed by the respective patentees. Further details regarding the coding in order to obtain information on the patent renewals can be found in the appendix of this paper in subsection 7.11.

In the subsequent analyses, selected descriptives on the evolvement of the renewal rate outcomes are provided.[47] Therefore, in a first step, the evolvement of the renewal shares in different technological sectors over time are depicted. It can be seen from the adjacent figure, that the overall renewal rates of the EP patents are very high and amount between 70-80% from 1995 to 2004. Afterwards, the renewal rate decreases sequentially in the two subsequent time windows. Previous literature found that the renewal rates of granted patents significantly decreased over time. For instance, it was found in an European context that more than half of the patents were canceled by the age of eight and only 25% of the patents survived the age of thirteen (Schankerman and Pakes 1986). These

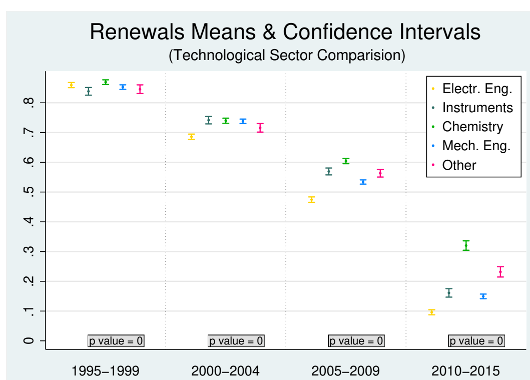


Figure 8.2

[45]Therefore, the European patent system is very fragmented which results in high enforcing costs of patents in Europe. The implementation of the so called community patent which would be unique for all European member states and automatically cover the whole geographical area like in the United States, has been discussed over the last decades and would substantially reduce the enforcement costs of a Patent in Europe (Harhoff et al. 2009).

[46]For these purposes, data on patent oppositions might be more insightful (Dechezleprêtre et al. 2017).

[47]As the renewal variable is generated as an indicator variables, no additional summary statistic tables are provided in this subsection.

results were also backed by international comparisons (Schankerman 1998). Generalizing the findings from previous research for numerous countries, on average only 50 per cent of patents are alive 8 years after their grant and only around 15 per cent survive for their full statutory period of protection (Christie and Rotstein 2008). Consequently, these findings may contribute to explain that the overall share of patent renewals as depicted above decreases over time. Besides this, the sharp drop in the share of overall patent renewals in the most current time window is also attributable to the fact that patents which have just recently been granted did not have to be renewed yet. When the overall shares of renewed patents are considered, the share of new patents is relatively large compared to established and renewed patents. Consequently, as the current time edge is approached, the renewal share is likely to be driven by recently granted and not yet renewed patents.

In a next step, the renewal rates across the technological sectors are compared. From the figure above, it can be seen that these rates tend to be the lowest in the Electrical Engineering sector from 2000 until 2015. Besides this, the Chemistry sector tends to have the highest renewal rates in the different time frames considered. Besides this, the technological sectors are depicted by the same overall decreasing patterns over time which is also in line with considerations from previous literature (Christie and Rotstein 2008). In order to evaluate this notion in a more structural manner, the above figure contains an ANOVA test for the equality of the renewal rate means regarding the different technological sectors within the four time windows (1995-1999, 2000-2004, 2005-2009, 2010-2015) considered. According to the null hypothesis of this statistical test, the means of the renewal outcomes should be the same in all five technological areas whilst the rejection of the null hypothesis leads to the conclusion that at least two technological sectors have different means. It can be seen that the p-values of the ANOVA test are zero in all four time windows, indicating that the differences of the renewal rate outcomes between the technological sectors are statistically highly significant over time. These findings are in line with findings from previous literature, which found in a European context that for instance the renewal rates in the Electronics sector were systematically lower than those in the Chemicals sector, which jointly with the Pharmaceuticals sector had the highest renewal rates (Schankerman 1998). Generalizing the findings from previous literature, patents from high technology sectors such as pharmaceuticals tend to have the highest renewal rates compared to patented inventions from the low-technology sectors (Christie and Rotstein 2008).

In a next step, descriptives containing analyses on renewal rates of patents from firms with different sizes are provided. The figure below depicts the evolvements of the renewal rate means in the four different time windows and a ANOVA test for the equality of their means in the different firm size categories within four time windows is conducted.[48] It can be seen that the p-values of this test are zero in all four time frames, which indicates that the differences of the renewal rates across the firm size classifications are statistically highly significant between 1995 until 2015. While medium-sized firms tend to have the highest renewal rates between 1995-2004, renewal rates were higher for large firms between 2005-2015. In line with some arguments from previous literature, these results indicate that the share of those patents which are expected to generate higher returns than their cost of renewals are comparable across firms with different sizes (OECD 2009).

[48] The utilized one-way ANOVA is a statistical test to compare the groups given that the outcome variable is continuous and that there are more than two groups (Kao and Green 2008).

In this context, it shall however be noted that the decision to keep or drop patents may not solely be indicative for the estimated private value of each individual patent but also be part of a broader corporate strategy. Firms might apply fencing strategies in order to generate hold-up problems for potential competitors or avoid own potential hold-up problems by establishing large patent portfolios in order to safeguard their investments in new technologies (Ziedonis 2004). These factors, which are related to overall profitability considerations of the respective firms but potentially less related to the value of individual patents, will potentially also influence firms' decisions to renew the patents of their portfolios. In this vein, the depicted renewal shares can be perceived as being indicative for firms' overall evaluations of their patent portfolios. In summary, it is interesting to note that these rates are not depicted by consistent level differences across small, medium and large firms.

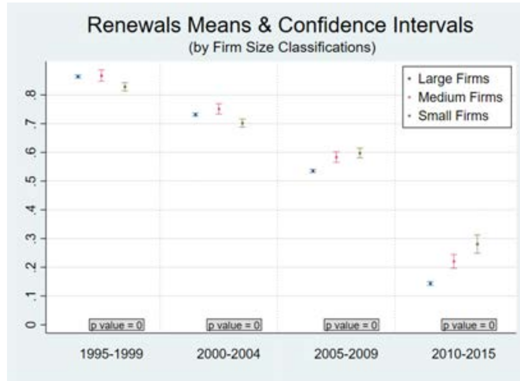


Figure 8.3

In a final set of analyses, the time series of renewal rate outcomes are depicted based on the firm country classification. For this purpose, the figure below provides the time series evolvements of the meaned renewal rate outcomes in the four time windows. Interestingly, it can be seen that there are no major time persistent differences in patent renewal rates across firms from different countries. Nevertheless, cross country variations in the renewal rates, which are also statistically highly significant based on analogous ANOVA tests, can be observed in each of the four time frames. Consequently, this implies that the renewal rates of the European patents which were filed by firms from different countries are different in each of the time windows considered, however no major and time persistent cross country differences in patent renewal rates can be carved out. Out of all these previous considerations, it follows that there are neither time persistent differences in the renewal rates across firms with different sizes nor across firms from different countries. The only dimension based on which time persistent differences could be established relate to the technological sectors. The appendix contains further descriptive figures and tables that provide analyses on the pairwise correlations of the meaned renewal rate outcomes across the above-discussed firm- and technology-specific dimensions. While subsection 6.8.1 provides insights as to whether and how the renewal rate outcomes of the firms' patents are correlated across the firm countries over the technological sectors in which these patents were filed in, subsection 6.8.2 contains analogous descriptive analyses regarding the way the conditional renewal rate means of the patent applications filed by firms from different countries are correlated across the three firm size classifications. Finally, subsection 6.8.3

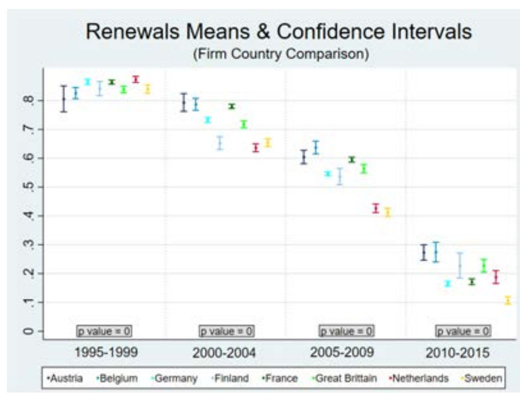


Figure 8.4

contains insights with respect to the evolvements of the renewal rate means across firms from different countries and the technological sectors of the corresponding patent filings.

4.3 Withdrawals

As a final measure, the withdrawals of patent applications are considered. According to the official Guide for applicants regarding how to get a European patent (hereinafter: EPO-Guide), the EPO establishes the state of the art of the patent application within the EPO procedure which contains information on the relevant prior art to the applicant and the examining devision (see recital 144 of the EPO 2019).
After the publication of this search report, the applicant has six months in order to file a request for examination. If this request is not filed, the application is deemed to be withdrawn (see recitals 146, 155 of the EPO 2019). The search report may contain evidence that the claimed invention is not novel or does not involve an inventive step. Indeed, it was shown that applicants tend to withdraw their applications when the result of the search report was negative, thereby reflecting an expected refusal of the application (Schneider 2007). It was shown by Harhoff and Wagner (2009) that 26.5% of the EPO patent applications are withdrawn by the applicants after receiving a sufficiently negative search report. If the applicant requests the subsequent examination, the application is examined by the patent office according to its novelty, the associated inventive step and the industrial applicability. During this examination process it is still possible for the applicant to withdraw the application (see recitals 156, 157 of the EPO 2019).

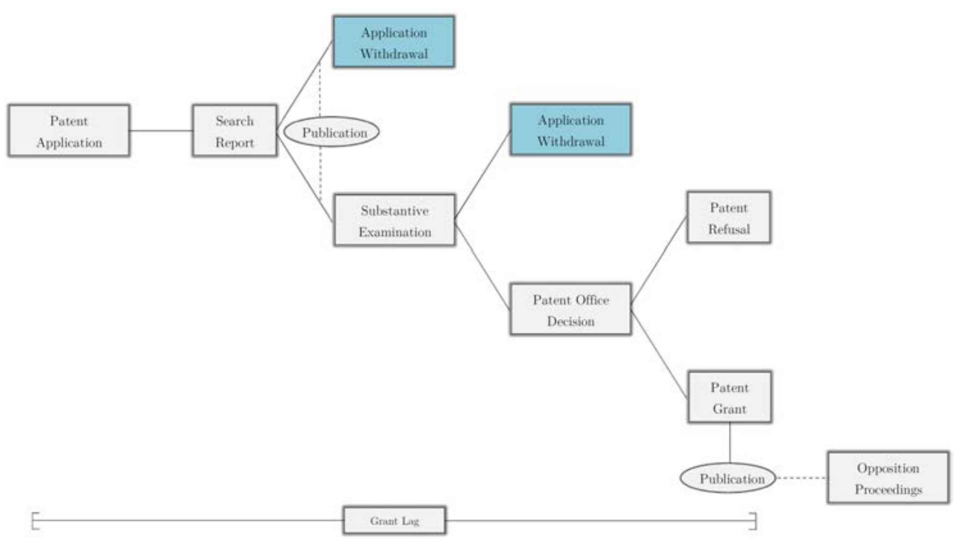


Figure 9.1: Patenting Process Overview

It is also argued in the literature that patent withdrawals can be interpreted as a signal which indicates that the patentee considers the continuation of the patent application process as too costly in relation to the expected marketability and the expected profit of the potentially granted patent due to the relative low quality of the underlying invention (Long and Wang 2019). Finally, it is also argued that potential delays in patent withdrawals are attributable to strategic considerations based on which the patentee wants to create insecurity for potential competitors through pending patents (Jell 2012), in particular because according to recital 144 of the EPO 2019 the search report of European patents filed at the EPO serves to provide information on the relevant prior art to the applicant to the public. The outcomes of the patent withrawal variable utilized in this subsections are either 1 or 0, indicating whether a particular patent application was withdrawn (=1) or not (=0). Therefore, meaned values of the withdrawal variable can be interpreted as percentage values regarding the share of patent applications that have been withdrawn.[49] Details regarding the respective coding procedure in order to obtain information on the patent withdrawals can be found in section 5 above as well as in subsection 7.11 of this paper.

The subsequent analyses depict selected descriptives on the evolvement of the withdrawal outcomes of those patents that can be linked to the Amadeus database based on the matching algorithm provided by Peruzzi et al. (2014).[50] In a first step, the evolvement of the patent withdrawal rates in different technological sectors over time are provided. Based on the adjacent figure, it can be seen that the time series of the meaned withdrawal outcomes of all filed patent applications tend to increase from 1995 until 2009 from around 15% to 32% and decrease in the time window from 2010 until 2015 to around 10%. The drop in withdrawal rates in the most recent time window can be attributed to the fact that after patent applications are filed, some time will pass before patentees decide whether to withdraw their applications or not. In line with Harhoff and Wagner (2009), this decision likely depends on the outcomes of the time consuming prior art search which is conducted by the patent examining authorities. Therefore, the decrease of the renewal rates in the most recent time window can be rationalized by these considerations. Apart from this, it is interesting to note that the withdrawal rates in the Electrical Engineering and Chemistry sector tend to be systematically higher than those in the Instruments and Mechanical Engineering sector. Such cross industry differences have also been established by previous literature. For instance, in a European context Schneider (2007) found for a set of Danish patent applications that the overall average withdrawal rates for the patent applications filed between 1978 until 1997 amounted to 29% with substantial variations over time and differences across technological sectors.[51] Besides this, Lazaridis and van Pottelsberghe de la Potterie (2007) who analyzed patent applications filed at the EPO from 1985 to 2004 found that overall about 35% of the patent applications were withdrawn by the applicants, while Schettino and Sterlacchini (2009) who considered all EPO applications from 1991 until 2004 which were contained in the OECD/EPO citations database found substantially lower overall withdrawal rates of about 24,5% with differences across the technological sectors. From these considerations, it follows that the magnitudes of the withdrawal rates depicted above are overall in line with the findings from previous

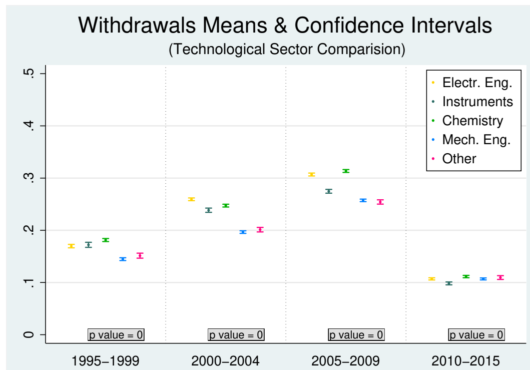


Figure 9.2

[49] As the withdrawal variable is generated based on this indicator scheme, no further summary statistic tables are provided in this subsection.

[50] As the withdrawal variable is generated as an indicator variables, no additional summary statistic tables are provided in this subsection.

[51] For instance, the withdrawal rate of the patent applications considered by Schneider (2007) amounted to approximately 50% in 1978 while it was only about 20% in 1990. Furthermore, the withdrawal rates were lowest in process engineering while they were the highest in Mechanical Engineering.

literature. In order to evaluate the differences in the withdrawal rates across the technological sectors in a more structural manner, the figure above contains an ANOVA test for the equality of the withdrawal rate means regarding the different technological sectors within the four time windows (1995-1999, 2000-2004, 2005-2009, 2010-2015) considered. According to the null hypothesis of this statistical test, the means of the withdrawal rate outcomes should be the same in all five technological areas whilst the rejection of the null hypothesis leads to the conclusion that at least two technological sectors have different means. From the figure above, it can be seen that the p-values of the ANOVA test are zero in all four time windows, indicating that the differences of the withdrawal rate outcomes between the technological sectors are indeed statistically highly significant over time.

In the next part, descriptive analyses on the withdrawal rate outcomes of the patent applications which were filed by firms with different sizes are provided. In order to classify the firms into size categories, information from Amadeus are utilized. Based on the classification scheme provided by the European Commission, firms are categorized as i) *small* if they have less than 50 employees and a turnover below 10 mEur, ii) *medium* if they have between 50 and 250 employees and a turnover between 10 - 50 mEur and iii) *large* if they have 250 or more employees and a turnover above 50 mEur.[52] The adjacent figure depicts the evolvements of the withdrawal rate means in the four different time windows and a ANOVA test for the equality of their means in the different firm size categories within four time windows is conducted. It can be seen that the p-values of this test are (close to) zero in all four time frames, which indicates that the differences of the withdrawal rates across the firm size classifications are statistically highly significant between 1995 and 2015. Besides this, no structural differences in the withdrawal rate outcomes can be observed across time as the relative orders of the withdrawal rate outcomes change over time between small, medium and large firms. In light of previous literature, these results appear to be somehow surprising as, for instance, analyses which are also based on Patstat data and cover a time range between 2000 and 2008 found that patents filed by small and medium sized firms were withdrawn more frequently than patents from large firms (Frietsch et al. 2013). Furthermore, also a study based on Norwegian entities found that applications were more often withdrawn by small and medium enterprises compared to those of large firms (Iversen and Kaloudis 2010). It is argued that smaller enterprises tend to overestimate the value of their inventions, do not possess adequate knowledge of the patent systems and might be attributed to litigation threats of larger companies, thereby contributing to a higher willingness to withdraw patent applications (Iversen and Kaloudis 2010, Schettino and Sterlacchini 2009). Based on the insights from the figure above, it is however interesting to note that the withdrawal rates of the firms analyzed in this paper tend to be the highest for large firms

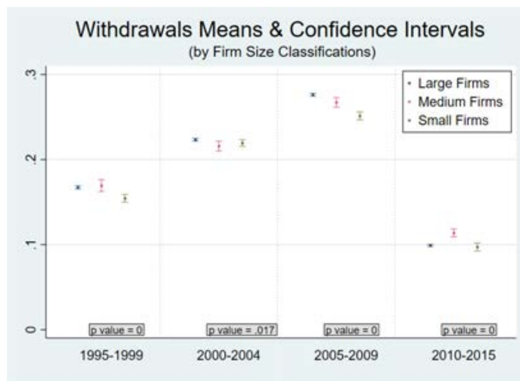


Figure 9.3

[52]See Recommendation of EU-Commission (2003) notified under the document number C(2003) 1422.

from 2000 until 2009, whilst they are never the highest for the small firms between 1995 until 2015. A final set of analyses depicts the time series of withdrawal outcomes based on the firm country classification. For this purpose, the adjacent figure provides the time series evolvements of the meaned withdrawal rate outcomes in the four time windows. It it interesting to note that the withdrawal rates of firms from Finland, Sweden and France tend to be systematically lower than those from British and German firms. Based on analogous ANOVA tests, these cross country variations in the withdrawal rates are also statistically highly significant in all time windows considered. In this vein, more sophisticated analyses on these cross-country differences in withdrawal rate outcomes are conducted in the appendix of this paper. These provide in subsections 6.9.1 to 6.9.3 pairwise correlation analyses of the meaned withdrawal rate outcomes across the above described firm- and technology-specific dimensions. Furthermore, the related figures in the appendix also contain the numerical magnitudes of the conditional mean outcomes across these dimensions which allow for determining whether substantial level-differences in the withdrawal rate outcomes exist.

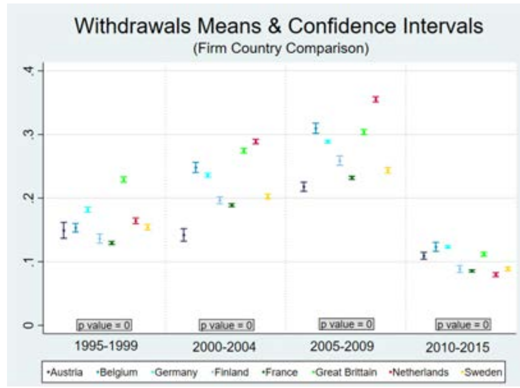


Figure 9.4

5 Conclusion

The paper at hand compiles and discusses selected empirical properties of numerous self-generated patent measures for European firms across multiple dimensions based on information from the Worldwide Patent Statistical Patstat database of the European Patent Office. It contains detailed descriptive analyses which are conducted for each patent measure from multiple perspectives, including evolvements over different technological sectors, firm sizes and countries. Beyond that, distributional analyses, statistical tests on differences in means as well as economic intuitions regarding the obtained empirical outcomes are provided and underpinned by the relevant related literature. The descriptive analyses regarding these patent measures are conducted for and limited to those patent applications which can be matched to financial data from the Amadeus database following the matching scheme introduced by Peruzzi et al. (2014). Therefore, the descriptives regarding the patent measures refer to European firms contained in Amadeus which can be linked to Patstat and, thereby, provide valuable insights for researchers in the field of corporate finance and innovation of European firms. The paper furthermore provides in depth documentations on the generating process of the above-described patent measures in order to facilitate the empirical work with Patstat, as it is also argued by previous literature that it is difficult to navigate in the wealth of data which are offered by Patstat. For this purpose, a comprehensible documentation on the generating process of the self-generated patent measures which is based on Structured Query Language (SQL) commands is contained in the appendix.

The descriptive findings of this paper are multi-fold and related to the specific characteristics of each patent measure. As described in the paper, the process for obtaining a patent involves several steps based on which the different patent measures which were discussed in this paper are derived. At first, the applicant needs to disclose the invention in sufficient detail which in particular includes the statement on its *claims*. The descriptive findings regarding this measure indicate that the established fluctuations and distributional properties of the number of claims over time and across technological sectors are related to the introduction of institutional changes in the patent claim fee structure. Furthermore, each patent document contains information on the technology fields concerned, i.e. the technological domain which a particular invention is attributed to. Given that patented inventions may fall into more than one technological domain, the *patent scope* variable indicates the technological breadth of a patented invention. According to the considerations from the paper, the structural properties of the patent scope outcomes are partly related to revisions of the underlying classification scheme. Additionally, time persistent variations in the patent scope outcomes across patent applications from different sectors were established. Above these findings and based on the consideration that each patent application needs to contain citations of previous related patents and scientific literature, the paper finds distinguished properties regarding the contained *backward citations* within patent applications from the Chemistry sector as well as for firms from different size classifications.

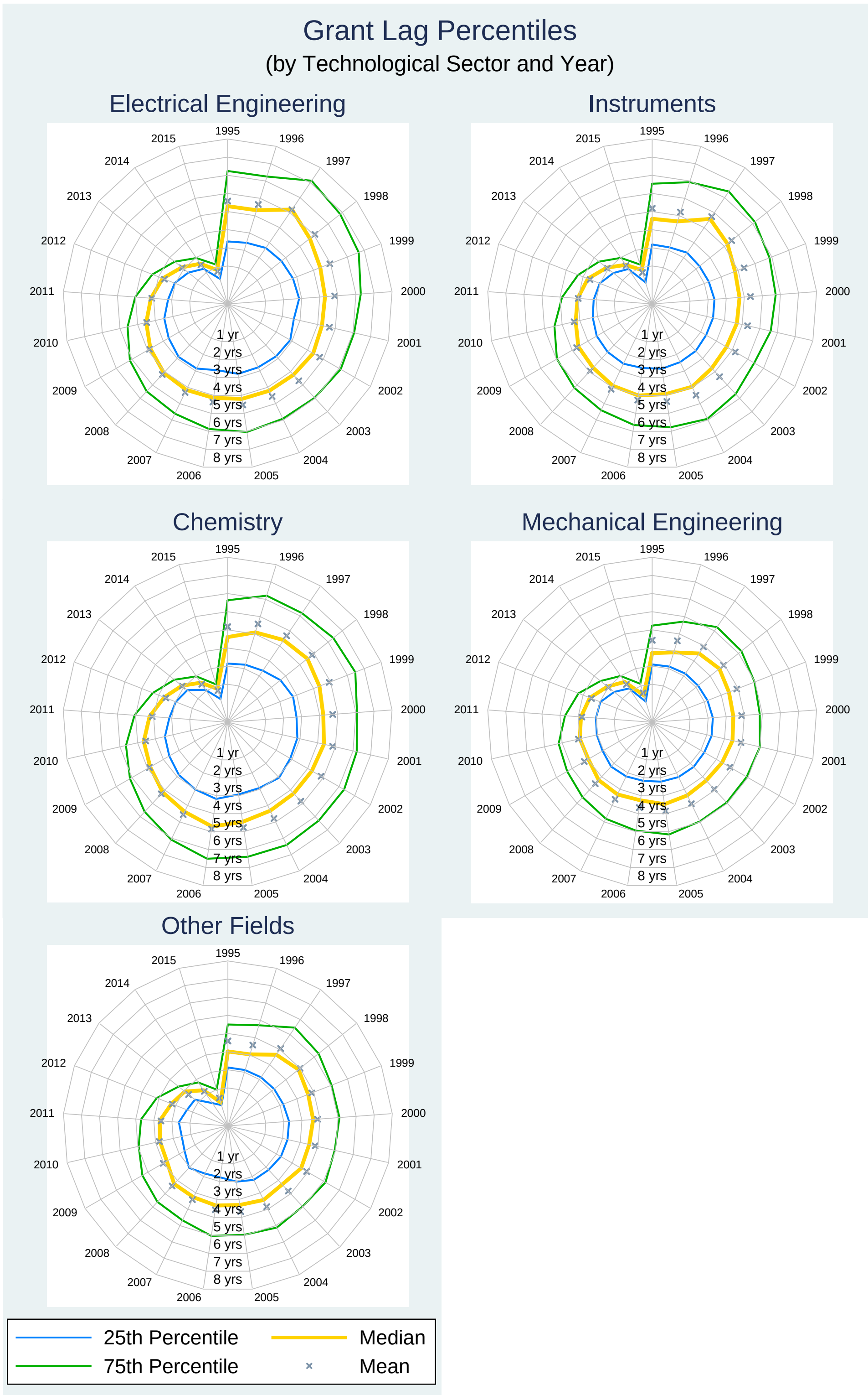
Based on the further course of the application process, information on the fate of the patent are obtained and properties of the derived patent measures are analyzed in the remainder of the paper. The patent can be granted or refused by the patent authority and depending on the length of this granting process the *grant lag* variable can be derived. The paper shows that the grant lag variable suffers from timeliness as the current time edge is approached and discusses differences in grant durations across technological sectors by pointing to differences in associated complexities of the underlying inventions. Besides this, the patent can also be *withdrawn* by the applicant himself. The findings of the paper reveal that the associated withdrawal rates vary substantially over time, technological sector and firm size classification. Once published, a filed patent can also be cited by other patent documents, which refers to its *forward citations*. The paper provides inter alia evidence that the forward citations of the firms' patents are shown to differ across the technological sectors considered. Besides this, the forward citation outcomes are depicted by a decreasing pattern as the current time edge is approached. Finally, after a patent is granted, it may be potentially *opposed* by external agents. The opposition rates for the set of European firms are relatively high compared to the findings from previous literature, which is arguably related to the corporate European perspective.

Summarizing, the analyses conducted in this paper contain valuable insights on the properties of multiple patent measures which are related to European firms' patenting activities. Some of the measures presented in this paper are insightful with respect to the technological aspects, while other measures are informative regarding the procedural, legal and value aspects of the underlying inventions. The descriptive findings, the detailed overviews on the generating process of each measure, as well as the contained background from previous related analyses contribute to reduce the perceived complexity of the rich universe of patent data from Patstat such that interested researchers can apply, adjust and refine the insights from this paper in future patent-related research projects.

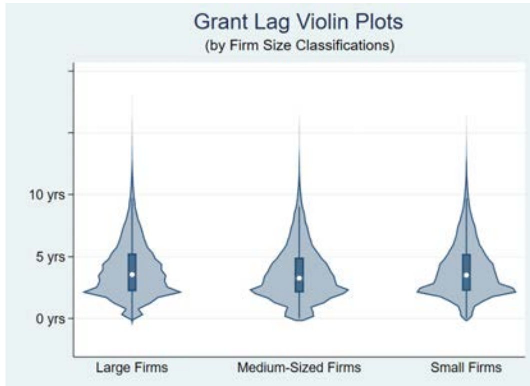
6 Appendix 1 - Additional Descriptives

6.1 Grant Lag - Figures and Tables

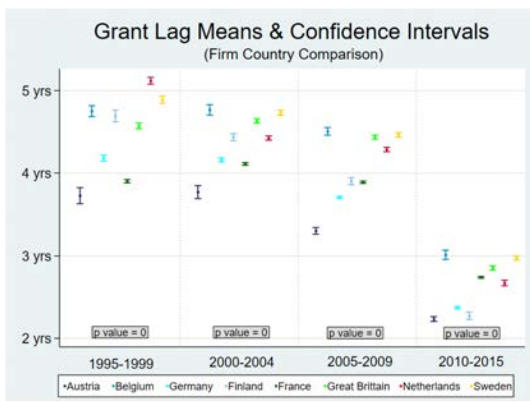
6.1.1 Grant Lag: Technological Sector



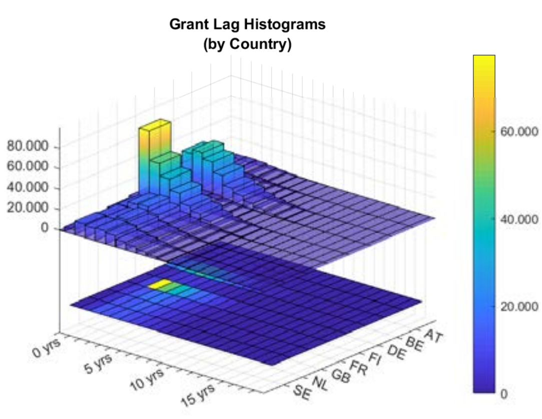
6.1.2 Grant Lag: Firm Size

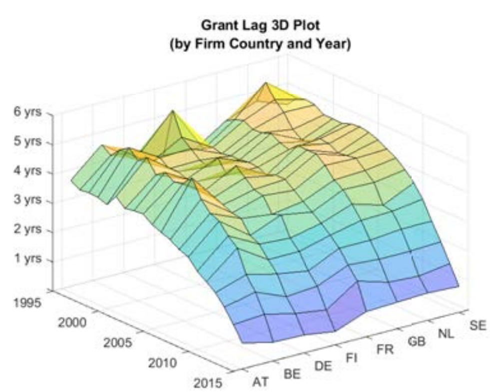


6.1.3 Grant Lag: Firm Country (1)



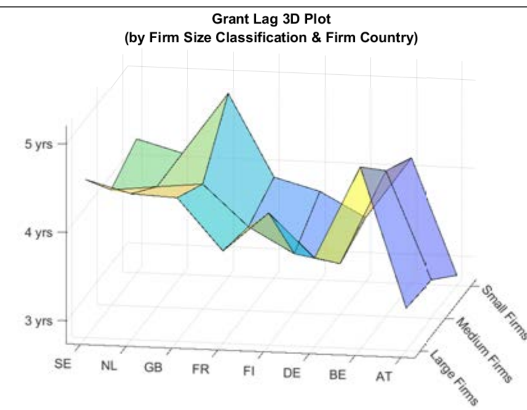
6.1.4 Grant Lag: Firm Country (2)





6.1.5 Grant Lag: Pairwise Correlation - Firm Size & Firm Country

Based on the considerations from the paper, the subsequent figure depicts the pairwise correlations of the conditional mean outcomes of the grant lag variable across different firm countries and firm size combinations. More precisely, the following figure provides insights as to whether the conditional firm country grant lag means are correlated across the three firm size classifications. For instance, it is possible that the above-established differences in the firms' patents grant lag means for the different firm countries are partly related to the size of the firms which filed the respective patents. These differences would be observable in the magnitudes of the respective conditional means, which are contained in the plot below and based on which the correlation coefficients are calculated. Besides this, these differences between the countries could also be driven by substantial differences in grant durations across the firm size classifications considered, which could be depicted by low correlation coefficients of the related conditional means. On the other hand, a high pairwise correlation of the meaned grant lag outcomes between large and medium firms would imply that large and medium-sized firms are affected similarly in their grant durations irrespectively of the countries in which these firms are located in.



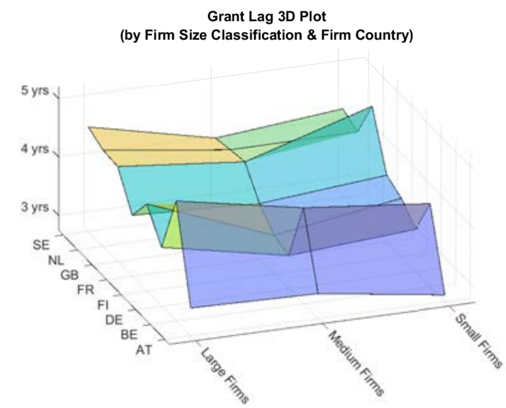
Grant Lag - Pairwise Correlations
[over Firm Country]

Variables	(1)	(2)	(3)
(1) Large Firms	1.000		
(2) Medium Firms	0.873*	1.000	
(3) Small Firms	0.812*	0.851*	1.000

From the above figure, it can be seen that the pairwise correlations of meaned grant lag outcomes are highly significant over the different firm countries in all three firm size classifications.[53].Therefore, while large, medium and small firms have for instance higher grant durations in Austria, firms in all these size classifications tend to have lower grant durations in Belgium or in Germany. These results therefore indicate

[53]The star in the table indicates significance at the 5 percent level.

that grant durations across firm size classifications are highly correlated over firm countries. As soon as the perspective is changed, the result becomes different. The next figure analyzes whether the grant lag means for firms of different sizes are correlated over different firm-country locations. For instance, a high pairwise correlation of the meaned grant lag outcomes across the firms from two countries would imply that firms from these countries are on average affected similarly in their grant durations over different firm size classifications. From the figure below, it can be inferred that the pairwise correlations of meaned grant lag outcomes are barely significant and often negative over the different firm size classifications in the different firm country classifications. Therefore, while firms from Great Britain have for instance higher grant durations for large firms compared to medium-sized firms and lower grant durations compared to small firms, the opposite tend to hold true for firms from Belgium which results in a negative correlation coefficient for firms from these two countries. These results indicate that grant durations across firm countries are rarely correlated over the three firm size classifications.

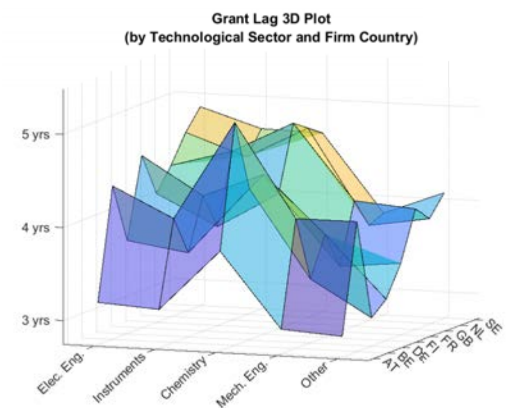


Grant Lag - Pairwise Correlations
[over Firm Size Classifications]

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Austria	1.000							
(2) Belgium	0.842	1.000						
(3) Germany	0.286	0.757	1.000					
(4) Finland	0.229	0.718	0.998*	1.000				
(5) France	-0.807	-0.362	0.335	0.390	1.000			
(6) Great Brittain	-0.901	-0.525	0.158	0.216	0.983	1.000		
(7) Netherlands	0.574	0.925	0.949	0.929	0.021	-0.162	1.000	
(8) Sweden	0.204	0.699	0.996	1.000*	0.413	0.241	0.919	1.000

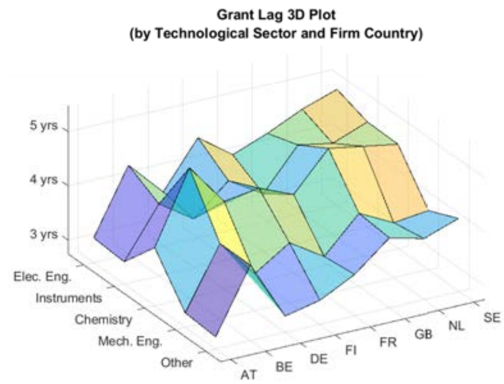
Summarizing, from the above figures, it can be seen that while grant lag means are highly correlated for small, medium and big firms across different firm countries, there is barely significant correlation of the grant lag outcomes for firms from different countries across different firm size classifications. The underlying reason for this descriptive finding may be a fruitful area for future research. Potentially, the differences in grant lag means for the different firm countries are partly related to the technological sectors in which the respective patent applications are filed in. For instance, it could be possible that firms from one country are particularly time-efficient in getting their patent applications granted compared to firms from other countries across the different technological sectors considered. In order to investigate this issue, analogous figures for pairwise correlations between grant lag outcomes referring to firm countries and the technological sectors of the patent applications are depicted and attached in subsection 6.1.6. From these figures, it can be inferred that the grant lag outcomes in the different technological sectors are highly positively correlated across the firm countries. Additionally, the grant lag outcomes in the the different firm countries are also highly positively correlated across the technological sectors as can be seen from the figures in subsection 6.1.7 of the appendix. These evolvements of the conditional grant lag mean outcomes across the different dimensions provide room for further research.

6.1.6 Grant Lag: Pairwise Correlation - Firm Country & Technological Sector



Grant Lag - Pairwise Correlations
[over Technological Sectors]

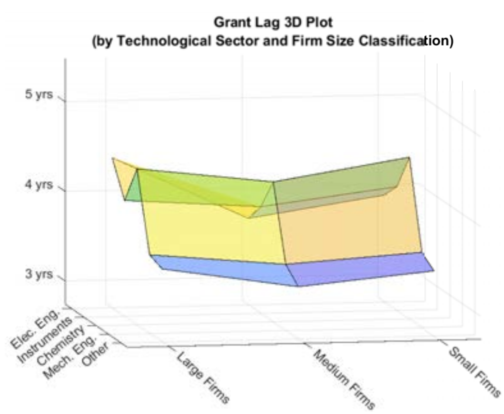
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Austria	1.000							
(2) Belgium	0.962*	1.000						
(3) Germany	0.945*	0.869	1.000					
(4) Finland	0.628	0.527	0.834	1.000				
(5) France	0.796	0.747	0.851	0.854	1.000			
(6) Great Brittain	0.918*	0.781	0.936*	0.739	0.830	1.000		
(7) Netherlands	0.776	0.681	0.844	0.858	0.984*	0.875	1.000	
(8) Sweden	0.537	0.422	0.636	0.791	0.906*	0.720	0.946*	1.000

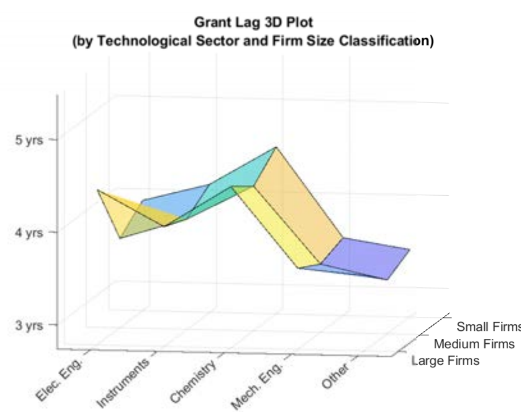


Grant Lag - Pairwise Correlations
[over Firm Country]

Variables	(1)	(2)	(3)	(4)	(5)
(1) Electr. Eng.	1.000				
(2) Instruments	0.939*	1.000			
(3) Chemistry	0.725*	0.765*	1.000		
(4) Mech. Eng.	0.805*	0.832*	0.948*	1.000	
(5) Other	0.727*	0.794*	0.847*	0.801*	1.000

6.1.7 Grant Lag: Pairwise Correlation - Firm Size & Technological Sector





Grant Lag - Pairwise Correlations
[over Firm Size Classifications]

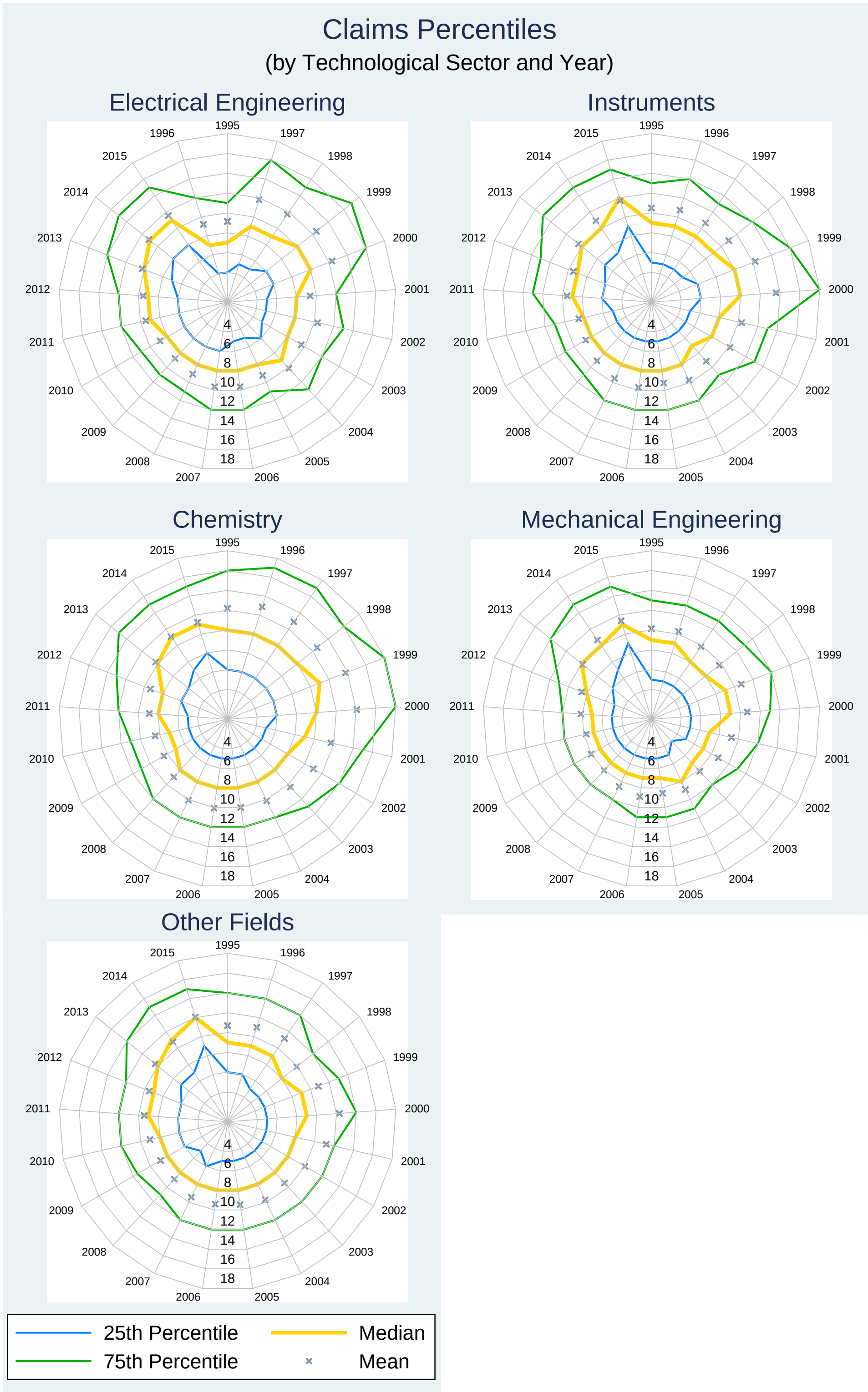
Variables	(1)	(2)	(3)	(4)	(5)
(1) Electr. Eng.	1.000				
(2) Instruments	0.349	1.000			
(3) Chemistry	0.552	0.974	1.000		
(4) Mech. Eng.	0.892	0.734	0.869	1.000	
(5) Other	0.939	0.650	0.805	0.993	1.000

Grant Lag - Pairwise Correlations
[over Technological Sectors]

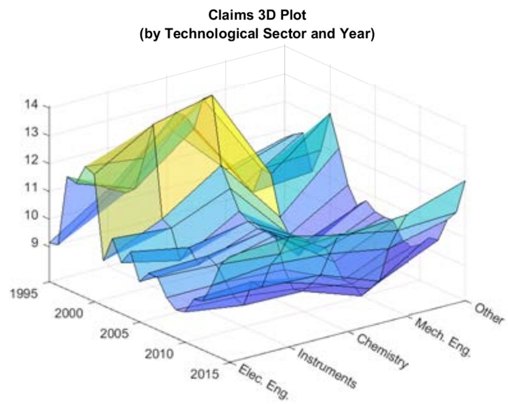
Variables	(1)	(2)	(3)
(1) Large Firms	1.000		
(2) Medium Firms	0.820	1.000	
(3) Small Firms	0.859	0.996*	1.000

6.2 Claims - Figures and Tables

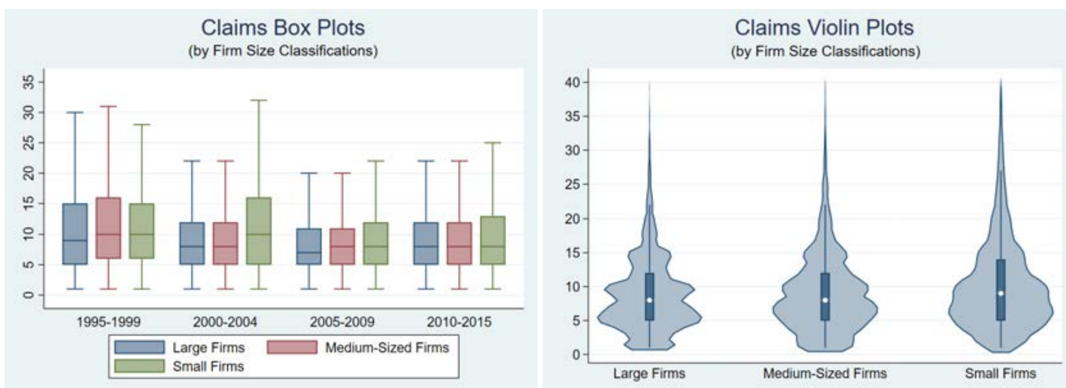
6.2.1 Claims: Technological Sector (1)



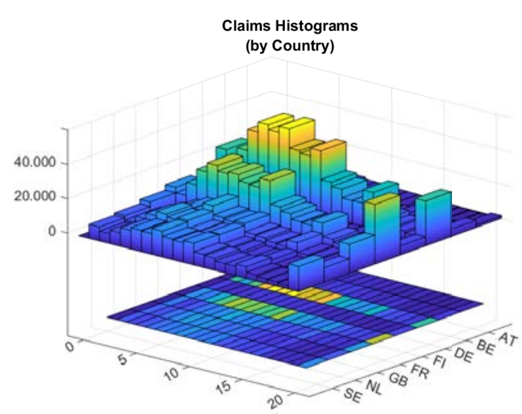
6.2.2 Claims: Technological Sector (2)



6.2.3 Claims: Firm Size Classification

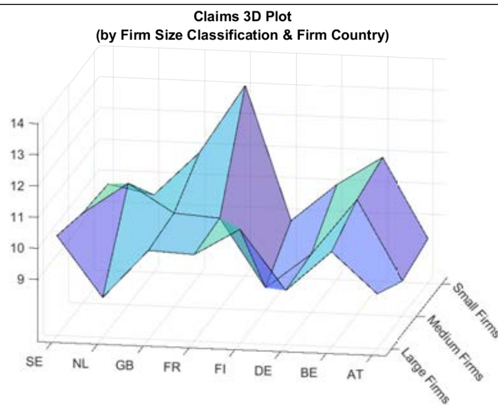


6.2.4 Claims: Firm Country



6.2.5 Claims: Pairwise Correlation - Firm Size & Firm Country

In order to get a better understanding for the above-established results regarding the patent claim outcomes, the following subsection provides follow-up analyses which depict the pairwise correlations of claims between the firm country classification and the firm size classification. For this purpose, conditional means on the claim outcomes are generated for each firm country and firm size combination. Based on these conditional means, the correlation coefficients are calculated which contain comparative insights regarding the claim evolvements across the firm countries and firm size combinations. While these analyses are rather exploratory in nature, they nevertheless may contain valuable insights for future research. For instance, the above-established differences in the firms' patents claim means across firms from different countries may be partly related to the size of the firms which filed and included the respective claims in the patent applications. These differences would be observable in the magnitudes of the respective conditional claim means. Besides this, these differences could also be partly driven by substantial differences in the claim outcomes across the different technological sectors, which would be reflected in low correlation coefficients of the related conditional means.



Claims - Pairwise Correlations
[over Firm Country]

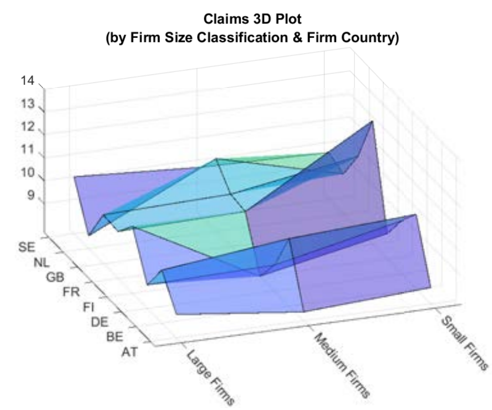
Variables	(1)	(2)	(3)
(1) Large Firms	1.000		
(2) Medium Firms	-0.152	1.000	
(3) Small Firms	0.221	0.521	1.000

From the above figure, it can be seen that the pairwise correlations of meaned claim outcomes are barely significant over the different firm countries in all three firm size classifications.[54] Besides this, the signs of the pairwise correlations vary across different firm size combinations. While the claim outcomes of small firms are positively correlated with those outcomes from medium as well as large firms across the different

[54] A star in the table would indicate significance at the 5 percent level.

countries, the claim outcomes from medium-sized firms tend to be negatively related to those from large firms across different countries.

As soon as the perspective is changed, the result however becomes different. The next figure analyzes whether the claim means for firms of different sizes are correlated over different firm-country locations. For instance, a high pairwise correlation of the meaned claim outcomes between two firm countries would imply that firms from these countries are affected similarly in the meaned claim outcomes across the different firm size classifications. From the figure below, it can be seen that the pairwise correlations of the meaned claim outcomes are highly positively or negatively significant over the different firm size categories for some countries while the significance disappears for other country comparisons. For instance, the claim outcomes for German, British and French firms have a high and significant positive correlation across the firm size categories, while the correlation between Belgian and Dutch firms across the firm size classifications is highly negative and significant. These results indicate that claim outcomes across firm countries have diverse correlation structures over the three firm size classifications.



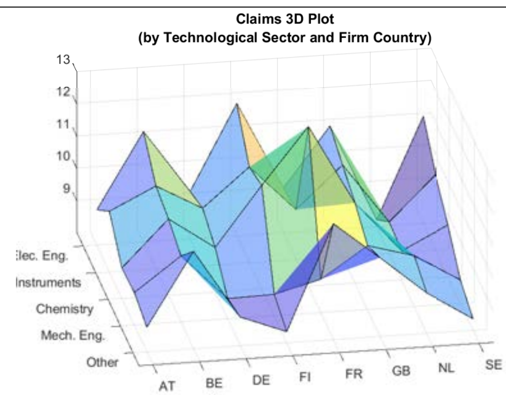
Claims - Pairwise Correlations
[over Firm Size Classifications]

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Austria	1.000							
(2) Belgium	-0.666	1.000						
(3) Germany	-0.095	0.806	1.000					
(4) Finland	0.992	-0.755	-0.220	1.000				
(5) France	-0.045	0.775	0.999*	-0.170	1.000			
(6) Great Brittain	-0.147	0.836	0.999*	-0.270	0.995	1.000		
(7) Netherlands	-0.998*	0.620	0.035	-0.983	-0.015	0.087	1.000	
(8) Sweden	0.733	-0.996	-0.747	0.813	-0.712	-0.780	-0.691	1.000

* shows significance at the .05 level

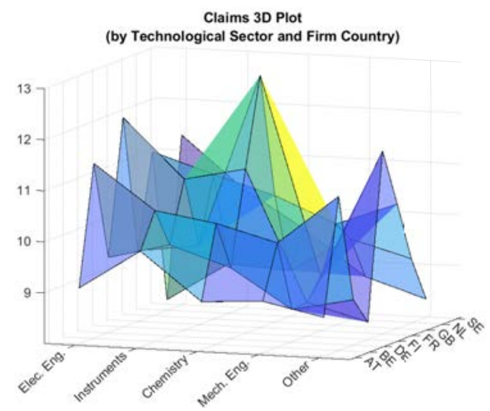
Summarizing from the above figures, it can be seen that while claim means are barely significantly correlated for small, medium and large firms across different firm countries, there exist significant positive as well as negative correlations of the claim outcomes for firms from different countries across different firm size classifications. The underlying reason for these descriptive findings may be a fruitful area for future research. The differences in claim mean outcomes for the different firm countries might potentially be related to the technological sectors in which the respective patent applications are filed in. For instance, it is possible that firms from one country have particular expertise and highly skilled human capital in certain technological sectors. This competitive advantage might have an effect on the formal definition of the scope of associated patent applications and thereby affect the number of claims for these particular firms, while firms from different countries in the same sector might behave differently in documenting their patent claims. In order to investigate this issue, analogous figures for pairwise correlations between claim outcomes referring to firm countries and the technological sectors of the patent applications are depicted and attached in subsection 6.2.6 of the appendix to this paper. From these figures, it can be inferred that the claim outcomes in the different technological sectors are barely significantly correlated across the firm countries. Additionally, the claim outcomes in the the different firm countries are with some exceptions also barely significantly correlated across the technological sectors. Further correlation analyses referring to the firm size classifications and the technological sectors of the patent claims can also be found in subsection 6.2.7. In conclusion, future research is needed in order to provide explanations to the above depicted descriptive findings regarding the claim outcomes across different structural dimensions.

6.2.6 Claims: Pairwise Correlation - Firm Country & Technological Sector



Claims - Pairwise Correlations
[over Firm Country]

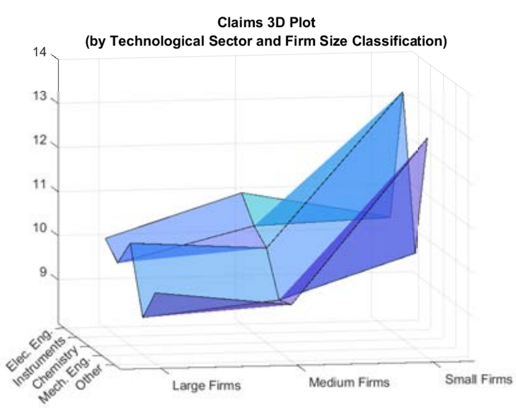
Variables	(1)	(2)	(3)	(4)	(5)
(1) Electr. Eng.	1.000				
(2) Instruments	0.952*	1.000			
(3) Chemistry	0.305	0.230	1.000		
(4) Mech. Eng.	0.050	0.100	-0.026	1.000	
(5) Other	-0.055	-0.067	0.622	0.629	1.000

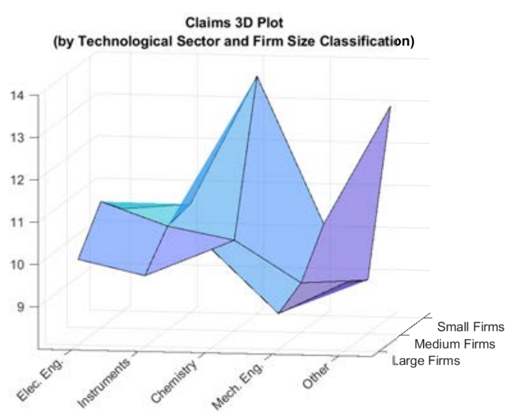


Claims - Pairwise Correlations
[over Technological Sectors]

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Austria	1.000							
(2) Belgium	-0.114	1.000						
(3) Germany	0.714	0.323	1.000					
(4) Finland	0.414	0.374	0.843	1.000				
(5) France	-0.464	-0.051	0.030	-0.012	1.000			
(6) Great Brittain	0.390	0.799	0.796	0.808	-0.155	1.000		
(7) Netherlands	-0.158	-0.757	-0.696	-0.882*	0.025	-0.938*	1.000	
(8) Sweden	0.508	0.505	0.794	0.935*	-0.330	0.889*	-0.897*	1.000

6.2.7 Claims: Pairwise Correlation - Firm Size & Technological Sector





Claims - Pairwise Correlations
[over Firm Size Classifications]

Variables	(1)	(2)	(3)	(4)	(5)
(1) Electr. Eng.	1.000				
(2) Instruments	0.730	1.000			
(3) Chemistry	-0.151	0.565	1.000		
(4) Mech. Eng.	0.134	0.775	0.959	1.000	
(5) Other	-0.186	0.535	0.999*	0.949	1.000

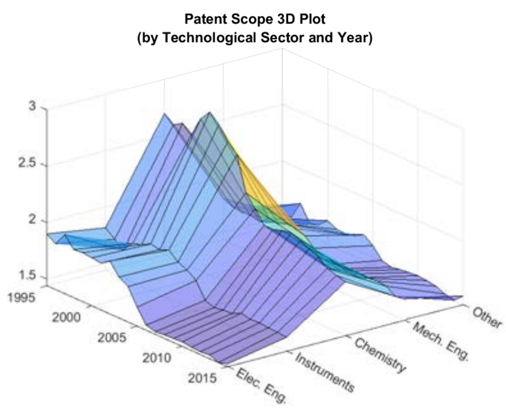
Claims - Pairwise Correlations
[over Technological Sectors]

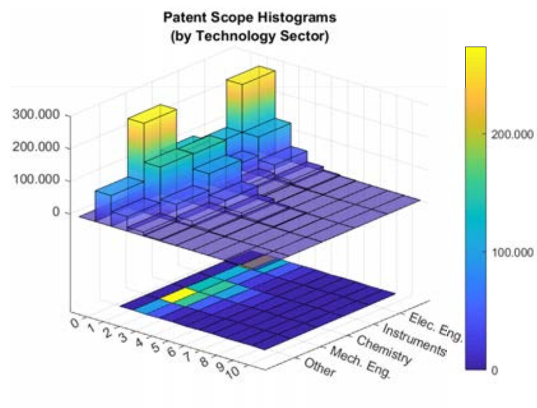
Variables	(1)	(2)	(3)
(1) Large Firms	1.000		
(2) Medium Firms	0.677	1.000	
(3) Small Firms	0.561	-0.228	1.000

6.3 Patent Scope - Figures and Tables

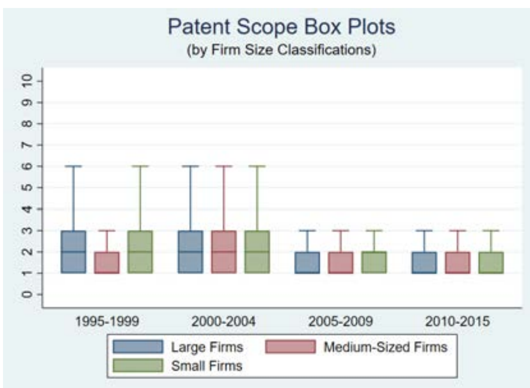
6.3.1 Patent Scope: Technological Sector (1)

6.3.2 Patent Scope: Technological Sector (2)

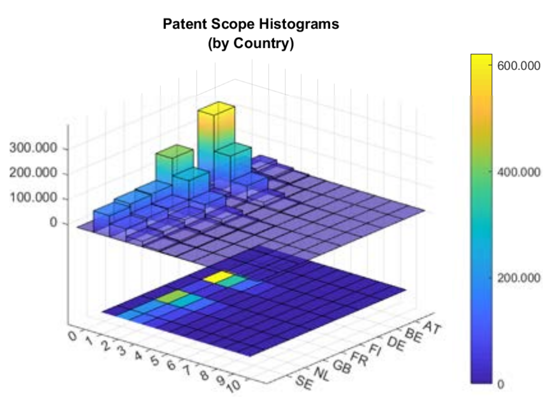




6.3.3 Patent Scope: Firm Size Classification

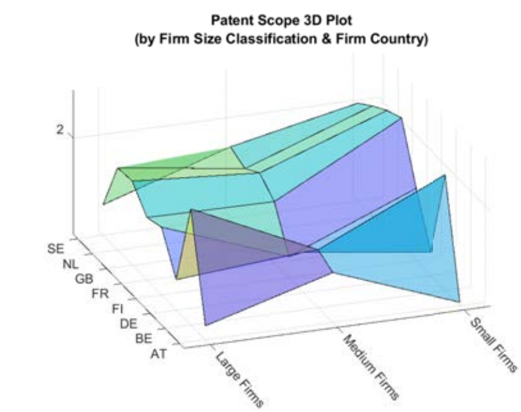


6.3.4 Patent Scope: Firm Country



6.3.5 Patent Scope: Pairwise Correlation - Firm Size & Firm Country

Based on the previous considerations contained in the paper, the descriptives from this subsection provide insights as to whether the conditional patent scope means for firms of different sizes are correlated across the different firm-country locations. For instance, a high pairwise correlation of the conditional patent scope means across two firm countries would imply that firms from these countries are affected similarly in their patent scope values over different firm size classifications. From the figure below, it can be seen that the pairwise correlation coefficients of the meaned patent scope outcomes are - depending on the countries considered - positive or negative. These correlations are, however, not statistically significant in most of the cases. Therefore, these results indicate that the patent scope outcomes across firm countries have diverse structures over the three firm size classifications and that no statistically significant systematic pattern can be depicted across the different countries.

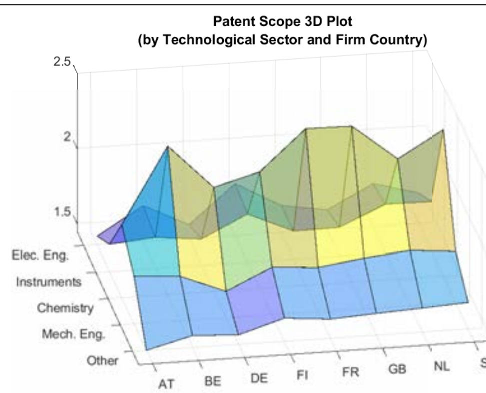


Patent Scope - Pairwise Correlations
[over Firm Size Classifications]

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Austria	1.000							
(2) Belgium	-0.975	1.000						
(3) Germany	0.983	-0.918	1.000					
(4) Finland	-0.989	0.997*	-0.946	1.000				
(5) France	-0.691	0.514	-0.812	0.579	1.000			
(6) Great Brittain	-0.803	0.651	-0.899	0.709	0.986	1.000		
(7) Netherlands	-0.914	0.802	-0.973	0.846	0.925	0.976	1.000	
(8) Sweden	-0.101	-0.122	-0.282	-0.044	0.789	0.674	0.495	1.000

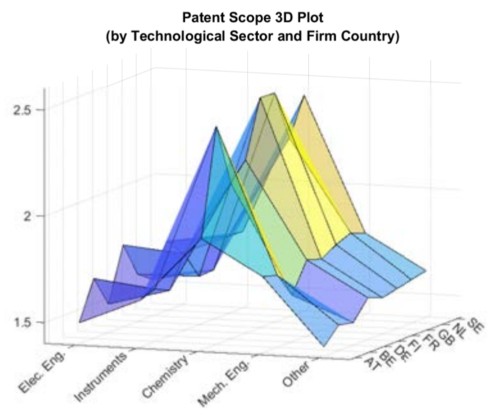
Overall, from the above figures it can be seen that while patent scope means are positively and significantly correlated for small and large firms across different firm countries, there exist barely significant correlations of the patent scope outcomes for firms from different countries across different firm size classifications. The underlying reason for these descriptive findings may be a fruitful area for future research. The differences in the patent scope mean outcomes for the different firm countries might potentially be related to the technological sectors in which the respective patent applications are filed in. In order to investigate this issue, analogous figures for pairwise correlations between patent scope outcomes referring to firm countries and the technological sectors of the patent applications are depicted and attached in subsection 6.3.6 of the appendix to this paper. From these figures, it can be inferred that the claim outcomes in the different technological sectors are positively and sometimes significantly correlated across the firm countries. Additionally, the patent scope correlations in the the different firm countries are highly positive and statistically significant across the technological sectors. Further correlation analyses referring to the firm size classifications and the technological sectors of the patent scope outcomes can also be found in the appendix to this paper in section 6.3.7. More research is needed in order to provide explanations to the above depicted descriptive findings regarding the patent scope outcomes across different structural dimensions.

6.3.6 Patent Scope: Correlation - Firm Country & Technology



Patent Scope - Pairwise Correlations
[over Firm Country]

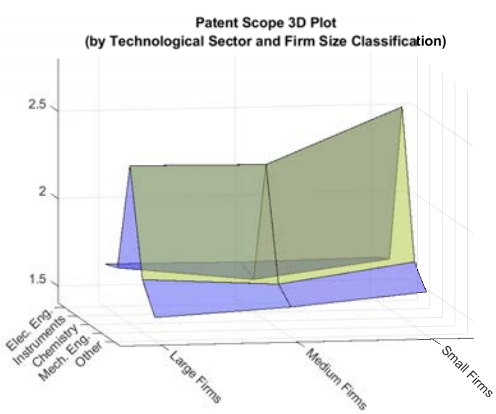
Variables	(1)	(2)	(3)	(4)	(5)
(1) Electr. Eng.	1.000				
(2) Instruments	0.787*	1.000			
(3) Chemistry	0.318	0.088	1.000		
(4) Mech. Eng.	0.432	0.569	0.242	1.000	
(5) Other	0.671	0.723*	0.663	0.486	1.000

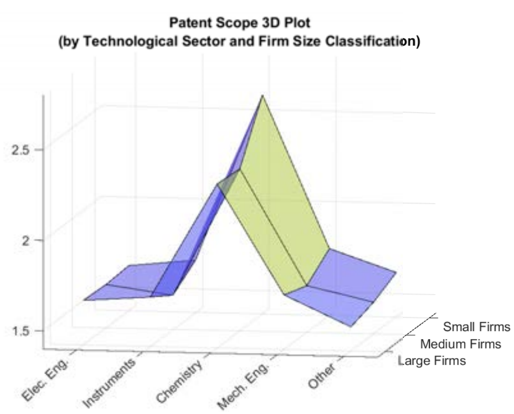


Patent Scope - Pairwise Correlations
[over Technological Sectors]

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Austria	1.000							
(2) Belgium	0.875	1.000						
(3) Germany	0.881*	0.988*	1.000					
(4) Finland	0.853	0.986*	0.967*	1.000				
(5) France	0.868	0.994*	0.993*	0.964*	1.000			
(6) Great Brittain	0.891*	0.983*	0.990*	0.944*	0.996*	1.000		
(7) Netherlands	0.918*	0.991*	0.986*	0.987*	0.980*	0.974*	1.000	
(8) Sweden	0.893*	0.985*	1.000*	0.962*	0.992*	0.991*	0.986*	1.000

6.3.7 Patent Scope: Correlation - Firm Size & Technological Sector





Patent Scope - Pairwise Correlations
[over Firm Size Classifications]

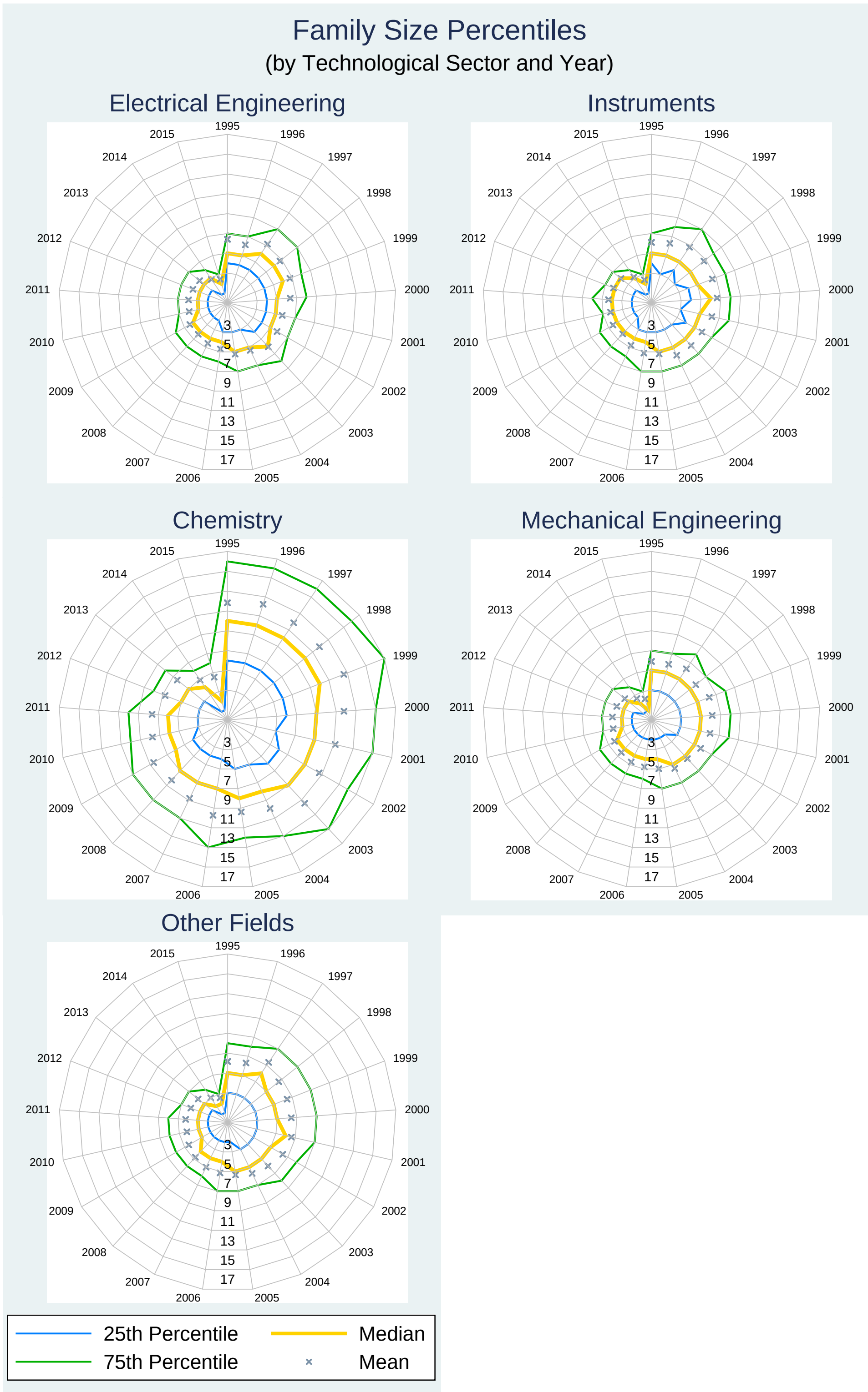
Variables	(1)	(2)	(3)	(4)	(5)
(1) Electr. Eng.	1.000				
(2) Instruments	0.944	1.000			
(3) Chemistry	0.868	0.656	1.000		
(4) Mech. Eng.	0.987	0.879	0.936	1.000	
(5) Other	0.593	0.295	0.915	0.715	1.000

Patent Scope - Pairwise Correlations
[over Technological Sectors]

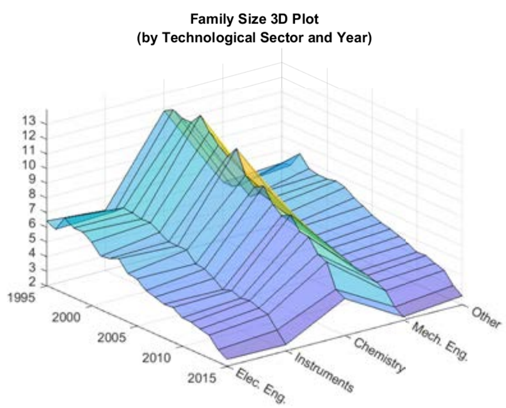
Variables	(1)	(2)	(3)
(1) Large Firms	1.000		
(2) Medium Firms	0.988*	1.000	
(3) Small Firms	0.989*	0.995*	1.000

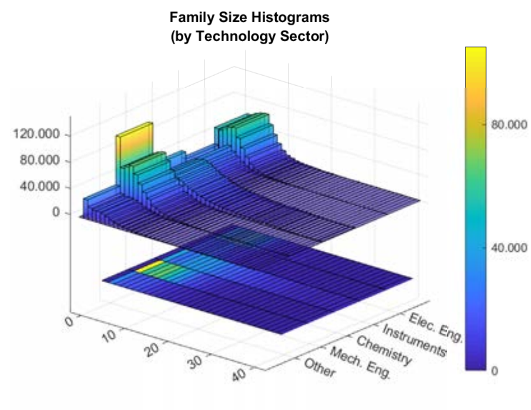
6.4 Family Size - Figures and Tables

6.4.1 Family Size: Technological Sector (1)

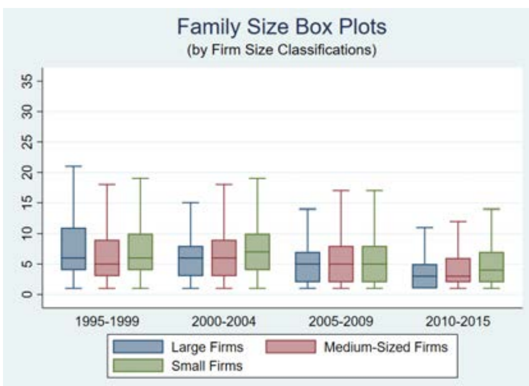


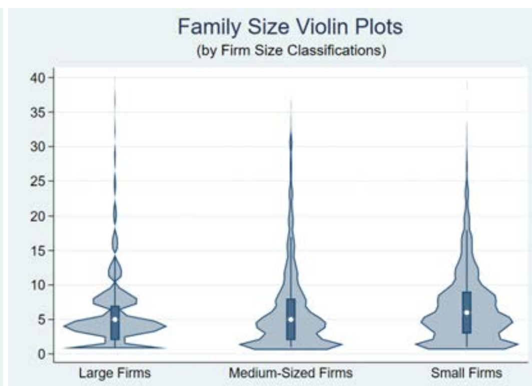
6.4.2 Family Size: Technological Sector (2)



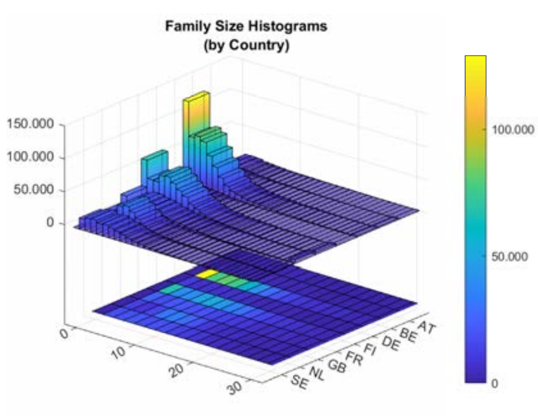


6.4.3 Family Size: Firm Size Classification



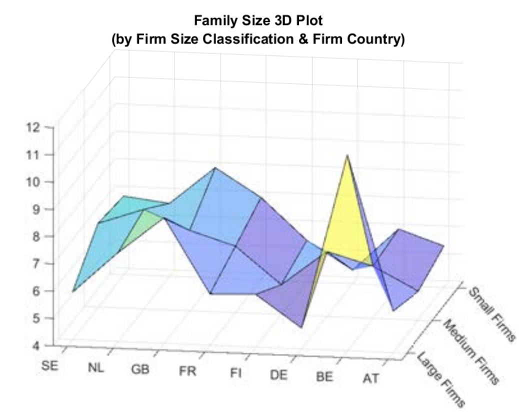


6.4.4 Family Size: Firm Country



6.4.5 Family Size: Pairwise Correlation - Firm Size & Firm Country

The subsequent figure depicts pairwise correlations of family size outcomes between the firm country classification and the firm size classification. More precisely, it is analyzed whether the firm country family size means are correlated over the three firm size classifications. It can be seen that the pairwise correlation values of the meaned family size outcomes are positive between all three firm size classifications over the different firm countries.[55] The family size outcomes between small, medium sized and large firms are, however, characterized by overall insignificant correlations, which indicates that family size outcomes between these firm categories have different outcomes across the firm countries considered. Therefore, this descriptive finding suggests that firms' locations tend to have rather little systematic impact on the firms' patent family size outcomes across different firm size categories and the above established time-persistent differences in family size outcomes in different countries are rather not driven by specific developments related to firms' sizes.



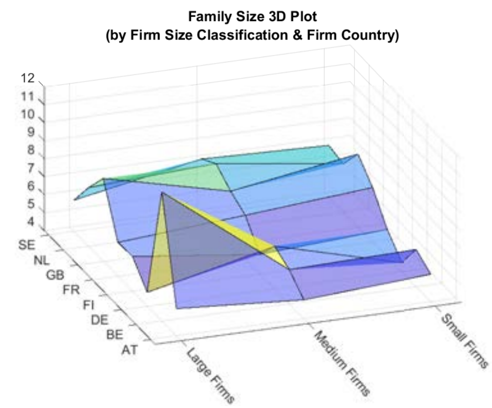
Family Size - Pairwise Correlations
[over Firm Country]

Variables	(1)	(2)	(3)
(1) Large Firms	1.000		
(2) Medium Firms	0.118	1.000	
(3) Small Firms	0.392	0.564	1.000

The perspective is changed in the next figure, in which the family size means for firms of different sizes are correlated over the firm-country locations. A high pairwise correlation of the meaned family size outcomes between two firm countries would imply that firms from these countries are affected similarly in their family size outcomes over different firm size classifications. When the outcomes from the correlation matrix below are considered, it can be seen that while the correlation coefficients range from highly positive to highly negative values between the firm countries, none of the coefficients is statistically different from

[55] A star in the table would indicate significance at the 5 percent level.

zero. Therefore, these results indicate that the family size outcomes across firm countries have diverse structures over the three firm size classifications and that no statistically significant systematic pattern can be depicted across the different countries. From the above figures, it can be seen that there exist barely significant correlations of the family size outcomes for firms from different countries across different firm size classifications. The underlying reasons for these descriptive findings constitute - in line with considerations from previous literature - a fruitful area for future research. Potentially, the differences in the meaned family size outcomes for the different firm countries are related to the technological sectors in which the respective patent applications are filed in.

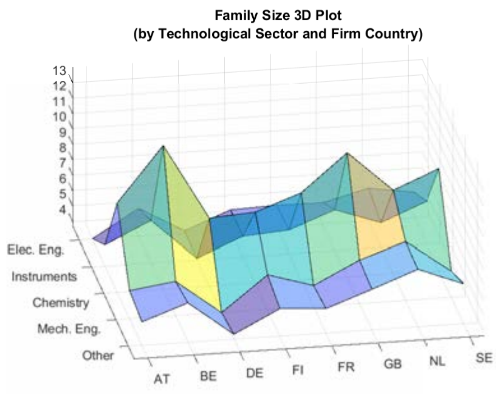


Family Size - Pairwise Correlations
[over Firm Size Classifications]

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Austria	1.000							
(2) Belgium	0.523	1.000						
(3) Germany	-0.992	-0.410	1.000					
(4) Finland	0.875	0.871	-0.805	1.000				
(5) France	0.020	-0.842	-0.148	-0.467	1.000			
(6) Great Brittain	0.945	0.774	-0.895	0.985	-0.309	1.000		
(7) Netherlands	-0.797	0.098	0.868	-0.405	-0.620	-0.555	1.000	
(8) Sweden	-0.613	-0.994	0.506	-0.919	0.778	-0.838	0.011	1.000

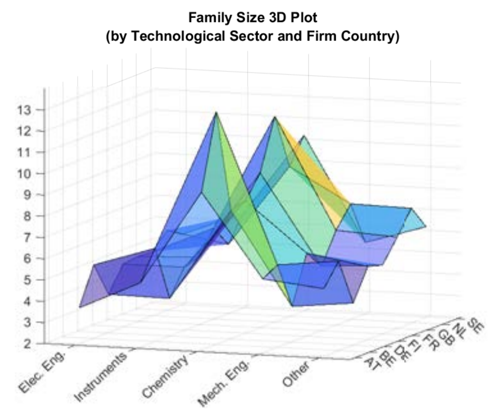
In order to investigate this issue, analogous figures for pairwise correlations between family size outcomes referring to firm countries and the technological sectors of the patent applications are depicted and attached in subsection 6.4.6 of the appendix. From the contained figures, it can be inferred that the family size outcomes in the different technological sectors are sometimes highly positively and significantly correlated across the firm countries, which suggests that technological specificities might contribute to explain the above-described persistent cross-country differences in family size values. Additionally, the family size correlations in the the different firm countries are highly positive and statistically significant across the technological sectors. Further correlation analyses referring to the firm size classifications and the technological sectors of the family size outcomes can also be found in the appendix to this paper in section 6.4.7. In conclusion, more research is needed in order to provide explanations to the above depicted descriptive findings regarding the family outcomes across different structural dimensions, particularly regarding the time-persistent differences of the family size outcomes across countries.

6.4.6 Family Size: Correlation - Firm Country & Technology



Family Size - Pairwise Correlations
[over Firm Country]

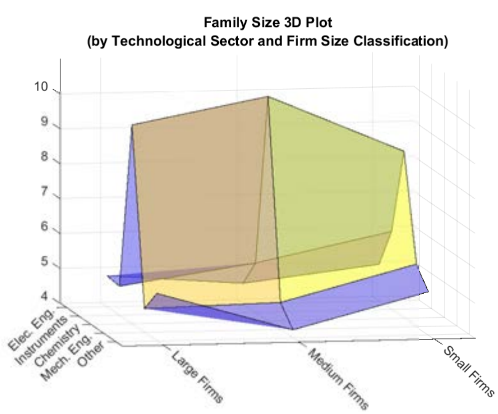
Variables	(1)	(2)	(3)	(4)	(5)
(1) Electr. Eng.	1.000				
(2) Instruments	0.652	1.000			
(3) Chemistry	0.418	0.839*	1.000		
(4) Mech. Eng.	0.687	0.529	0.327	1.000	
(5) Other	0.838*	0.700	0.460	0.918*	1.000

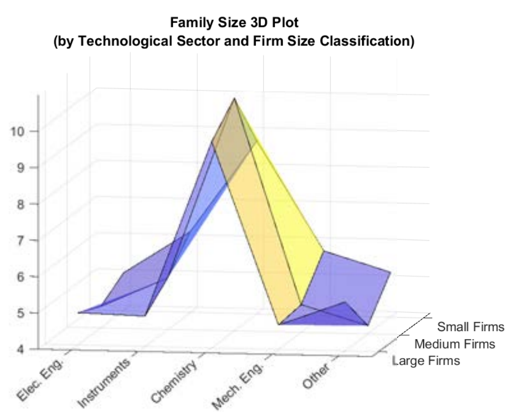


Family Size - Pairwise Correlations
[over Technological Sectors]

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Austria	1.000							
(2) Belgium	0.968*	1.000						
(3) Germany	0.944*	0.993*	1.000					
(4) Finland	0.974*	0.952*	0.951*	1.000				
(5) France	0.951*	0.996*	0.999*	0.952*	1.000			
(6) Great Brittain	0.994*	0.989*	0.972*	0.973*	0.977*	1.000		
(7) Netherlands	0.844	0.762	0.771	0.900*	0.765	0.815	1.000	
(8) Sweden	0.949*	0.988*	0.974*	0.904*	0.978*	0.972*	0.707	1.000

6.4.7 Family Size: Correlation - Firm Size & Technological Sector





Family Size - Pairwise Correlations
[over Firm Size Classifications]

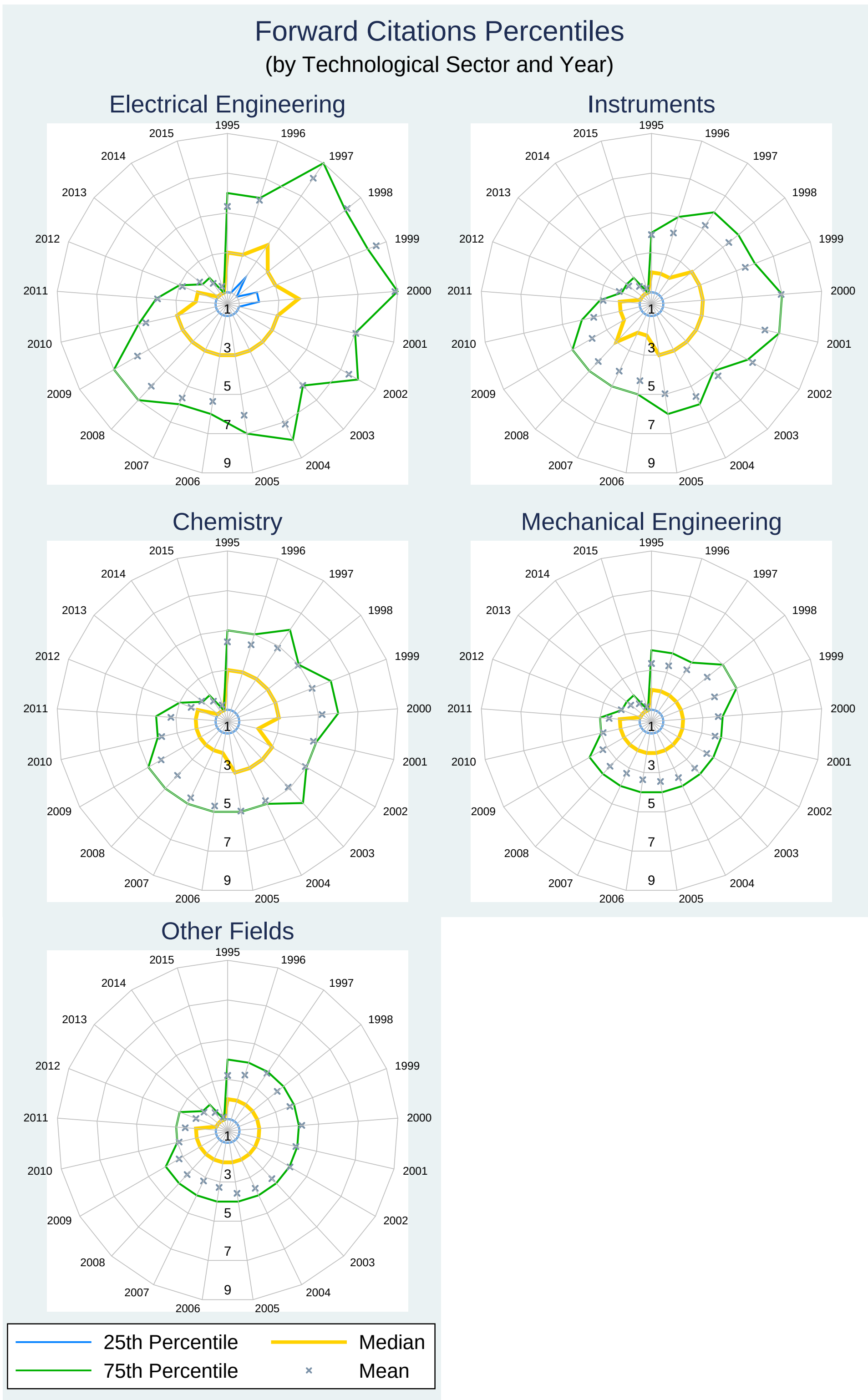
Variables	(1)	(2)	(3)	(4)	(5)
(1) Electr. Eng.	1.000				
(2) Instruments	0.440	1.000			
(3) Chemistry	-0.974	-0.633	1.000		
(4) Mech. Eng.	0.722	0.939	-0.860	1.000	
(5) Other	0.899	0.002	-0.776	0.346	1.000

Family Size - Pairwise Correlations
[over Technological Sectors]

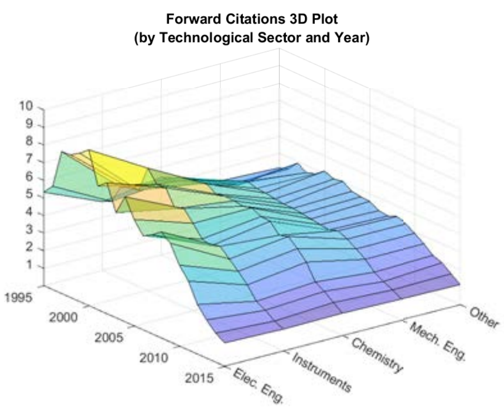
Variables	(1)	(2)	(3)
(1) Large Firms	1.000		
(2) Medium Firms	0.966*	1.000	
(3) Small Firms	0.926*	0.983*	1.000

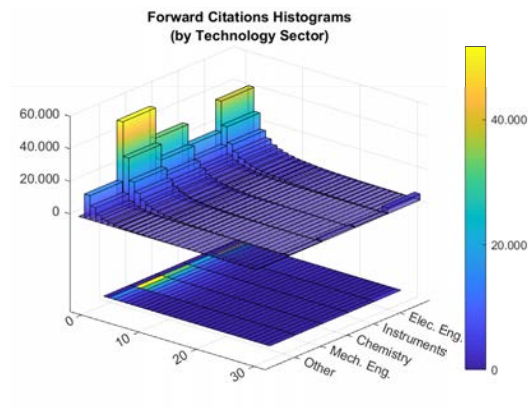
6.5 Forward Citations - Figures and Tables

6.5.1 Forward Citations: Technological Sector (1)

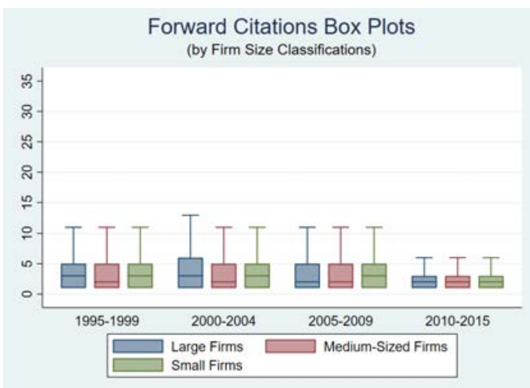


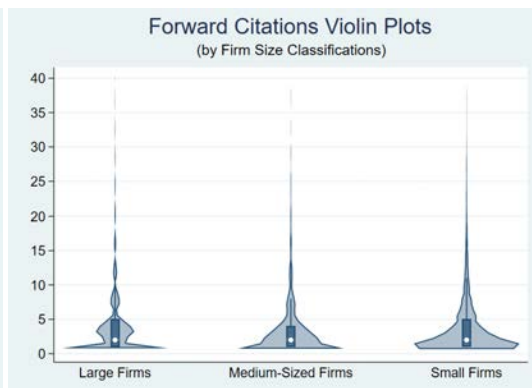
6.5.2 Forward Citations: Technological Sector (2)



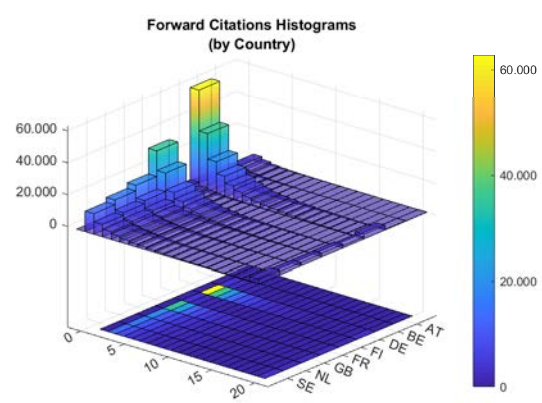


6.5.3 Forward Citations: Firm Size Classification



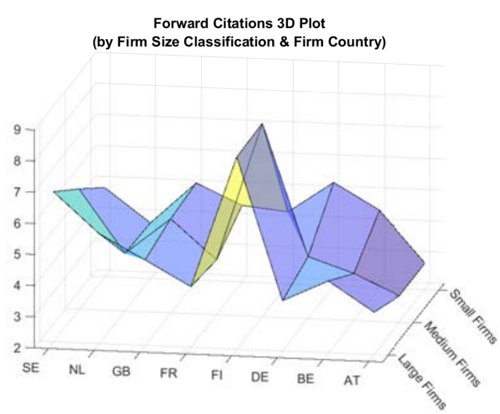


6.5.4 Forward Citations: Firm Country



6.5.5 Forward Citations: Pairwise Correlation - Firm Size & Firm Country

In order to get more insights regarding potential drivers of these persistent cross-country differences in their forward citations, more sophisticated analyses are provided in the following part of this paper. From the pairwise correlation values of the conditional mean forward citation outcomes below, it can be seen that there is a positive and highly significant correlation between the forward citation outcomes of medium and large firms across the different countries considered. On the other hand, no significant correlation towards small firms can be established.[56] This descriptive finding suggests that that the firms' locations have systematically similar impacts regarding the forward citations of medium and large firms while small firms are affected differently across countries regarding the forward citations they receive.

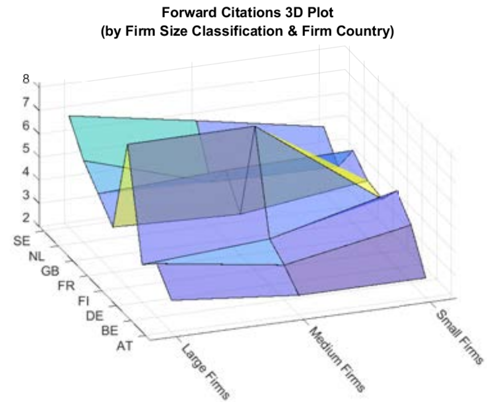


Forward Citations - Pairwise Correlations
[over Firm Country]

Variables	(1)	(2)	(3)
(1) Large Firms	1.000		
(2) Medium Firms	0.917*	1.000	
(3) Small Firms	0.130	0.320	1.000

In the next figure, the perspective is reversed and the correlations of forward citation means for firms of different sizes are analyzed across firm-country locations. A high pairwise correlation of the meaned forward citation outcomes between two firm countries would imply that firms from these countries are affected similarly in their forward citation outcomes over different firm size classifications. When the outcomes from the correlation matrix above are considered, it can be seen that while the correlation coefficients range from highly positive to highly negative values between the firm countries, only the correlation coefficient between firms from Austria and the Netherlands is highly positive and statistically significant. Therefore, these results indicate that the forward citation outcomes across firm countries have diverse structures over the three firm size classifications and statistically significant systematic pattern can be rarely depicted across the different countries.

[56] A star in the table would indicate significance at the 5 percent level.

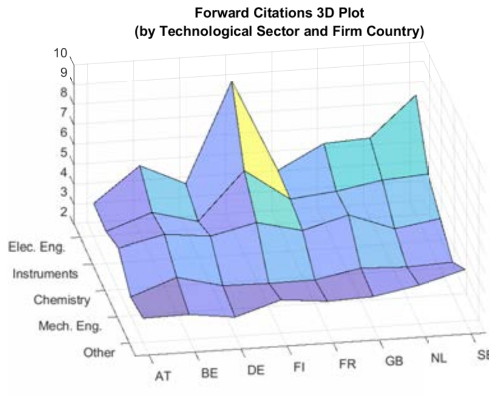


Forward Citations - Pairwise Correlations
[over Firm Size Classifications]

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Austria	1.000							
(2) Belgium	0.346	1.000						
(3) Germany	-0.662	0.474	1.000					
(4) Finland	0.489	-0.649	-0.977	1.000				
(5) France	-0.260	0.816	0.895	-0.969	1.000			
(6) Great Brittain	-0.961	-0.073	0.844	-0.711	0.517	1.000		
(7) Netherlands	0.999*	0.310	-0.691	0.522	-0.297	-0.971	1.000	
(8) Sweden	0.856	-0.188	-0.954	0.869	-0.721	-0.966	0.876	1.000

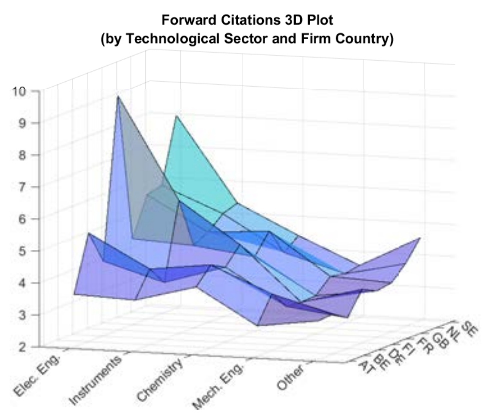
Finally, analogous figures for pairwise correlations between forward citation outcomes referring to firm countries and the technological sectors of the patent applications are depicted and attached in subsection 6.5.6 of this paper. From the included figures, it can be inferred that the forward citation outcomes in the different technological sectors are positively and significantly correlated across the firm countries with respect to Electrical Engineering and Instruments. Regarding other technological sectors, the correlation coefficients are insignificant. On the other hand, as the perspective is reversed, many country-related correlation coefficients are highly positive and statistically significant across the technological sectors considered. Further correlation analyses referring to the forward citation classifications and the technological sectors of the forward citation outcomes can also be found in the appendix to this paper in section 6.5.7.

6.5.6 Forward Citations: Correlation - Firm Country & Technology



Forward Citations - Pairwise Correlations
[over Firm Country]

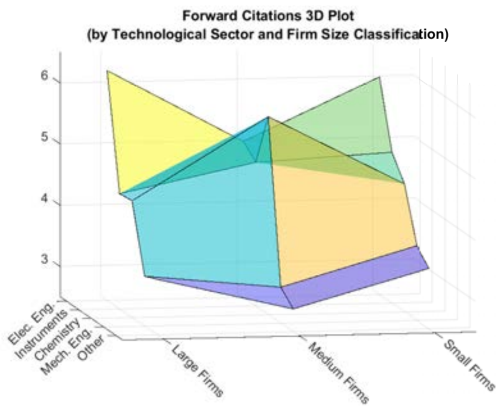
Variables	(1)	(2)	(3)	(4)	(5)
(1) Electr. Eng.	1.000				
(2) Instruments	0.945*	1.000			
(3) Chemistry	0.583	0.512	1.000		
(4) Mech. Eng.	0.274	0.289	0.367	1.000	
(5) Other	0.681	0.699	0.062	0.413	1.000

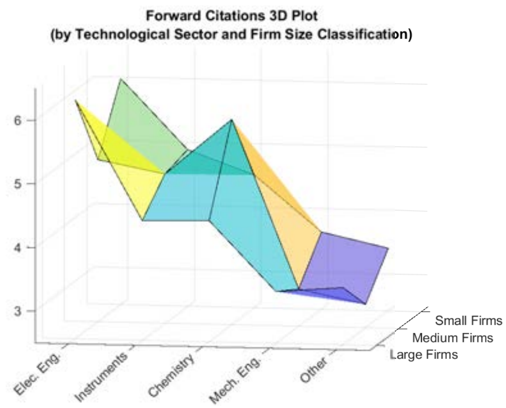


Forward Citations - Pairwise Correlations
[over Technological Sectors]

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Austria	1.000							
(2) Belgium	0.663	1.000						
(3) Germany	0.875	0.931*	1.000					
(4) Finland	0.490	0.893*	0.734	1.000				
(5) France	0.796	0.854	0.860	0.853	1.000			
(6) Great Brittain	0.736	0.977*	0.930*	0.931*	0.932*	1.000		
(7) Netherlands	0.424	0.803	0.629	0.973*	0.862	0.868	1.000	
(8) Sweden	0.365	0.790	0.597	0.974*	0.743	0.840	0.948*	1.000

6.5.7 Forward Citations: Correlation - Firm Size & Technological Sector





Forward Citations - Pairwise Correlations
[over Firm Size Classifications]

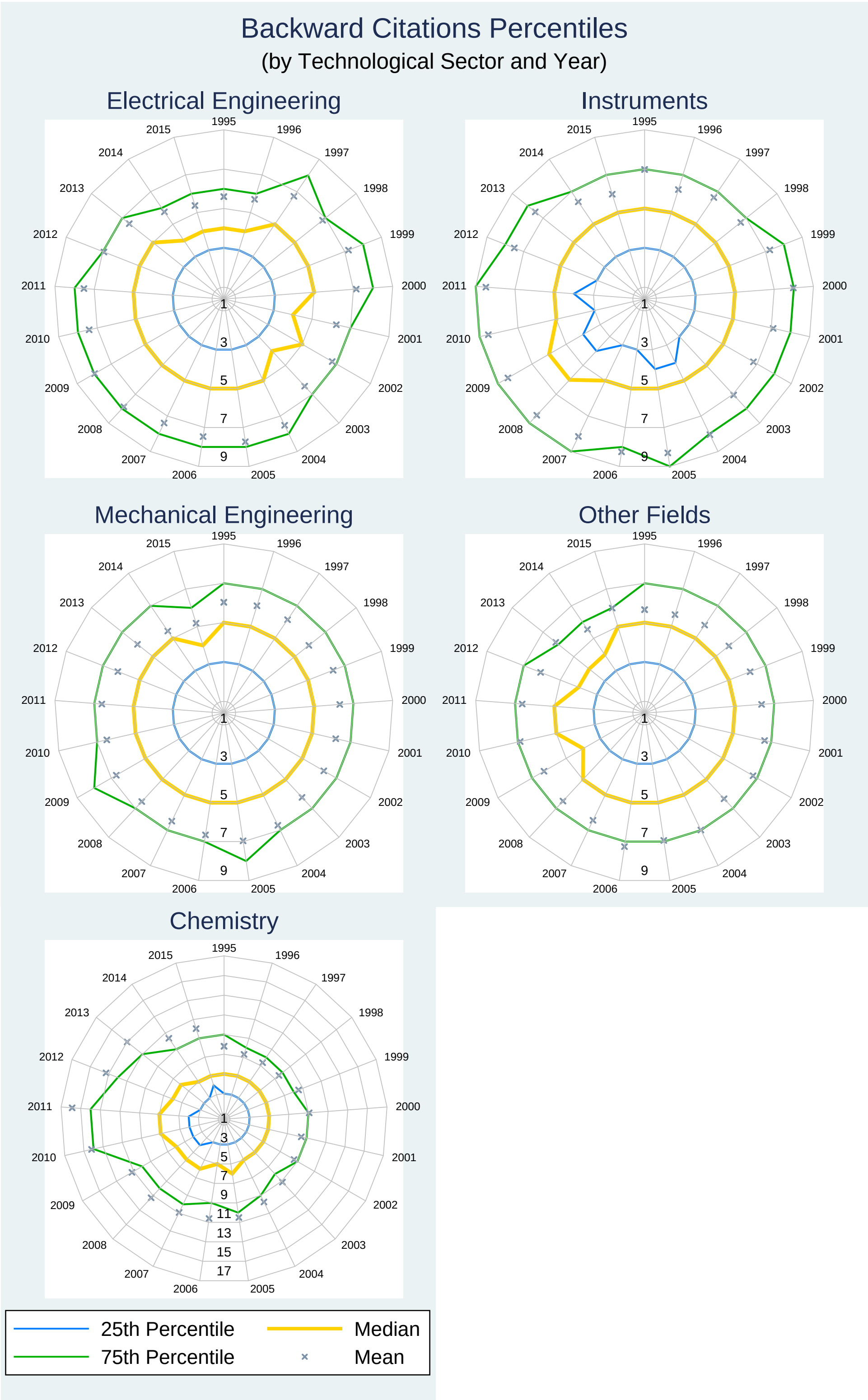
Variables	(1)	(2)	(3)	(4)	(5)
(1) Electr. Eng.	1.000				
(2) Instruments	-0.466	1.000			
(3) Chemistry	-1.00*	0.443	1.000		
(4) Mech. Eng.	0.669	0.347	-0.687	1.000	
(5) Other	0.961	-0.202	-0.968	0.849	1.000

Forward Citations - Pairwise Correlations
[over Technological Sectors]

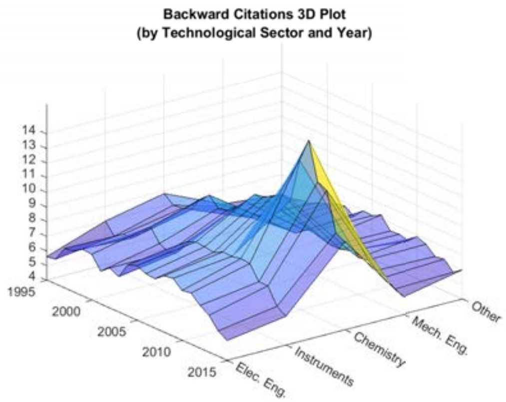
Variables	(1)	(2)	(3)
(1) Large Firms	1.000		
(2) Medium Firms	0.689	1.000	
(3) Small Firms	0.973*	0.752	1.000

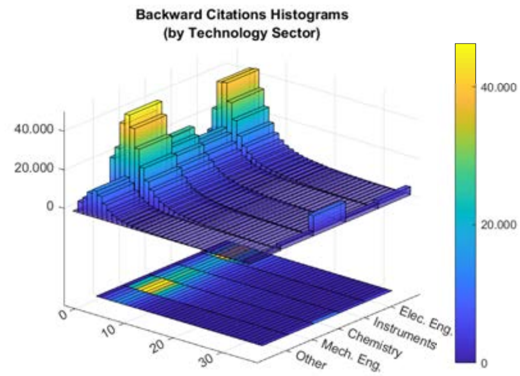
6.6 Backward Citations - Figures and Tables

6.6.1 Backward Citations: Technological Sector (1)

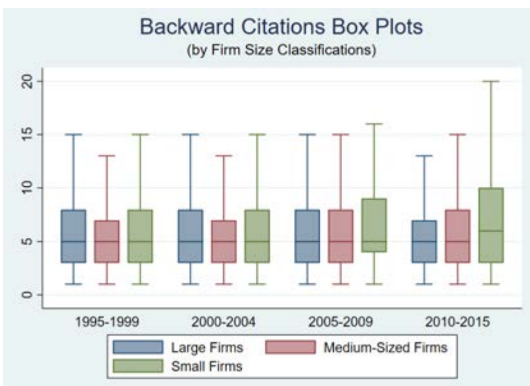


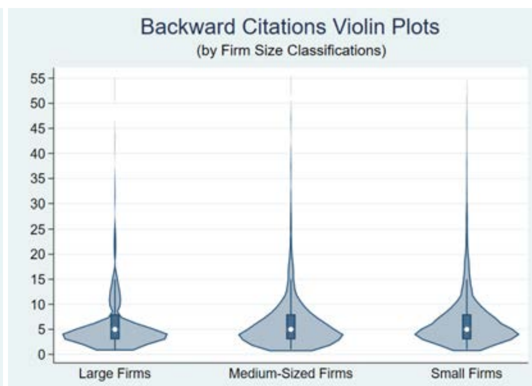
6.6.2 Backward Citations: Technological Sector (2)



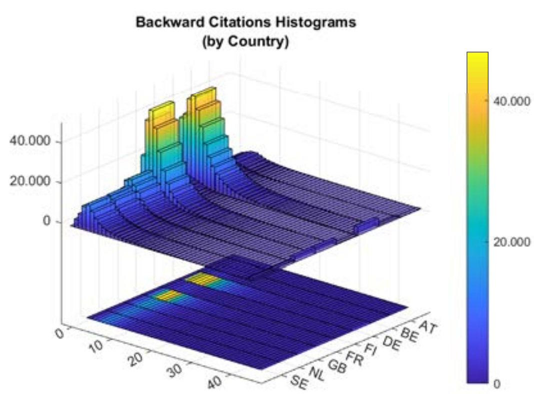


6.6.3 Backward Citations: Firm Size Classification



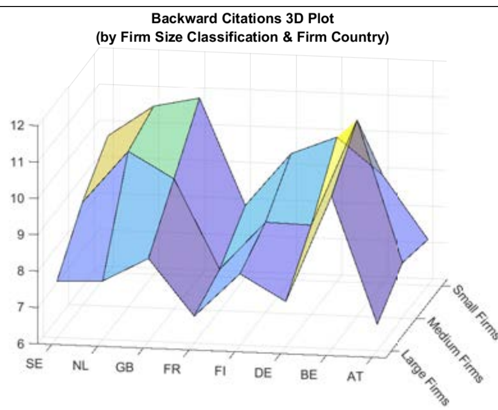


6.6.4 Backward Citations: Firm Country



6.6.5 Backward Citations: Correlation - Firm Size & Firm Country

In order to get more specific insights for potential drivers of the differences across the European firms, sophisticated analyses which go beyond the scope of this paper should analyze the backward citation outcomes conditional on the different application authorities. Nevertheless, in order to get more insights regarding potential drivers of these cross-country differences in their backward citations, the subsequent figure depicts the pairwise correlations of backward citation outcomes between the firm country and the firm size classification.[57] It is analyzed whether the firm country backward citation means are correlated over the three firm size classifications. A high pairwise correlation of the backward citation outcomes between large and medium firms would imply that large and medium-sized firms are affected similarly regarding their backward citation outcomes irrespectively of the countries in which these firms are located in. From the pairwise correlation values of the meaned backward citation outcomes below, it can be seen that there is a positive and highly significant correlation between the backward citation outcomes of medium and large firms across the different countries considered. On the other hand, no significant correlation towards small firms can be established.[58] This descriptive finding suggests that that firms' locations have systematically similar impacts on backward citation of medium and large firms while small firms are affected differently across countries regarding the forward citations they receive.



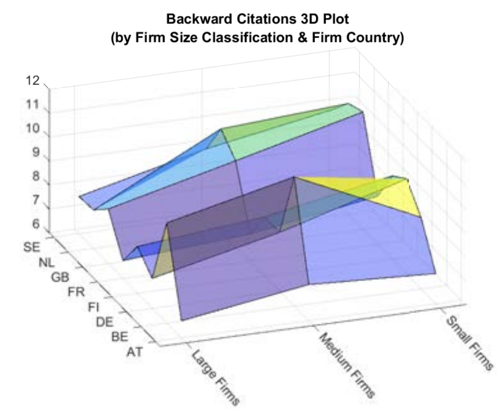
Backward Citations - Pairwise Correlations
[over Firm Country]

Variables	(1)	(2)	(3)
(1) Large Firms	1.000		
(2) Medium Firms	0.872*	1.000	
(3) Small Firms	0.297	0.551	1.000

[57]Further descriptives, which depict histogram plots of the backward citation outcomes in different countries, can be found in the appendix of this paper in subsection 6.6.4.

[58]A star in the table would indicate significance at the 5 percent level.

In a next step, the perspective is reversed and the correlations of backward citation means for firms of different sizes are analyzed across the different firm-country locations. A high pairwise correlation of the meaned backward citation outcomes between two firm countries would imply that firms from these countries are affected similarly in their backward citation outcomes over different firm size classifications. When the outcomes from the correlation matrix below are considered, it can be seen that while the correlation coefficients range from highly positive to highly negative values between the firm countries, only the correlation coefficient between firms from France and Finland as well as from Germany and Great Britain are highly positive and statistically significant. These results therefore indicate that the backward citation outcomes across firm countries have rather diverse structures over the three firm size classifications and statistically significant systematic pattern can be depicted rarely across the different firm countries.



Backward Citations - Pairwise Correlations
[over Firm Size Classifications]

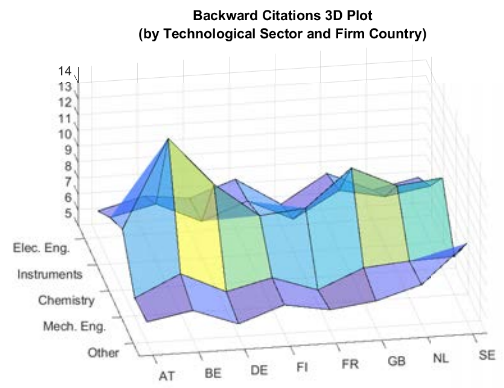
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Austria	1.000							
(2) Belgium	0.317	1.000						
(3) Germany	0.611	-0.557	1.000					
(4) Finland	0.521	-0.645	0.994	1.000				
(5) France	0.492	-0.670	0.990	0.999*	1.000			
(6) Great Brittain	0.658	-0.506	0.998*	0.985	0.979	1.000		
(7) Netherlands	0.910	-0.105	0.884	0.828	0.808	0.911	1.000	
(8) Sweden	0.727	-0.421	0.988	0.965	0.956	0.995	0.946	1.000

In a final step, analogous figures for pairwise correlations between backward citation outcomes referring to firm countries and the technological sectors of the patent applications are depicted and attached in subsection 6.6.6 of this paper. From these figures, it can be inferred that the backward citation outcomes in the different technological sectors are positively and significantly correlated across the firm countries with respect to Electrical Engineering and Instruments as well as with respect to Mechanical Engineering and Instruments. Therefore, patents from these sectors are affected similarly in their backward citation outcomes across the firms from different countries. Regarding other technological sectors, the correlation coefficients are insignificant. On the other hand, as the perspective is reversed, many country-related correlation coefficients are highly positive and statistically significant across the technological sectors considered.

Further correlation analyses referring to the backward citation classifications and the technological sectors of the backward citation outcomes can be found in the appendix to this paper in section 6.6.7.

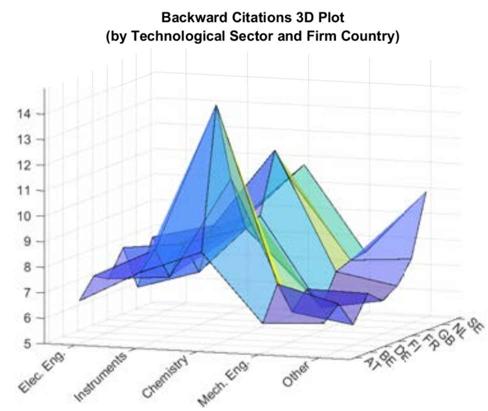
In summary, the underlying reasons for the established descriptive findings provide room for further and more sophisticated analyses, in particular when the evolvements of the backward citation means in the Chemistry sector as well as the established differences across the firm countries are considered.

6.6.6 Backward Citations: Correlation - Firm Country & Technology



Backward Citations - Pairwise Correlations
[over Firm Country]

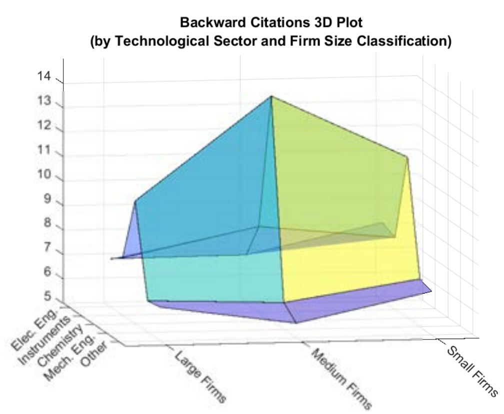
Variables	(1)	(2)	(3)	(4)	(5)
(1) Electr. Eng.	1.000				
(2) Instruments	0.763*	1.000			
(3) Chemistry	0.308	0.410	1.000		
(4) Mech. Eng.	0.568	0.865*	0.577	1.000	
(5) Other	0.196	0.524	0.051	0.647	1.000

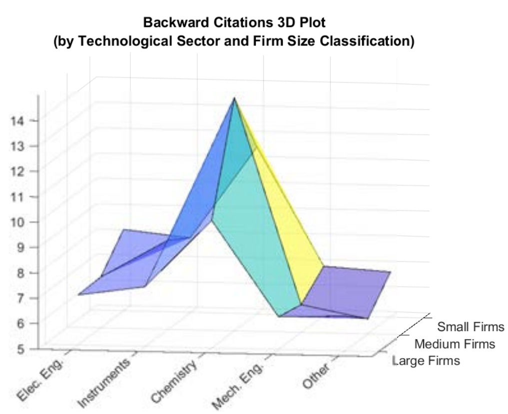


Backward Citations - Pairwise Correlations
[over Technological Sectors]

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Austria	1.000							
(2) Belgium	0.892*	1.000						
(3) Germany	0.904*	0.985*	1.000					
(4) Finland	0.924*	0.796	0.871	1.000				
(5) France	0.935*	0.980*	0.974*	0.835	1.000			
(6) Great Brittain	0.943*	0.969*	0.992*	0.919*	0.967*	1.000		
(7) Netherlands	0.888*	0.970*	0.922*	0.708	0.971*	0.908*	1.000	
(8) Sweden	0.604	0.669	0.604	0.364	0.752	0.563	0.791	1.000

6.6.7 Backward Citations: Correlation - Firm Size & Technological Sector





Backward Citations - Pairwise Correlations
[over Firm Size Classifications]

Variables	(1)	(2)	(3)	(4)	(5)
(1) Electr. Eng.	1.000				
(2) Instruments	0.044	1.000			
(3) Chemistry	-0.114	0.988	1.000		
(4) Mech. Eng.	0.970	-0.200	-0.351	1.000	
(5) Other	0.745	-0.634	-0.748	0.884	1.000

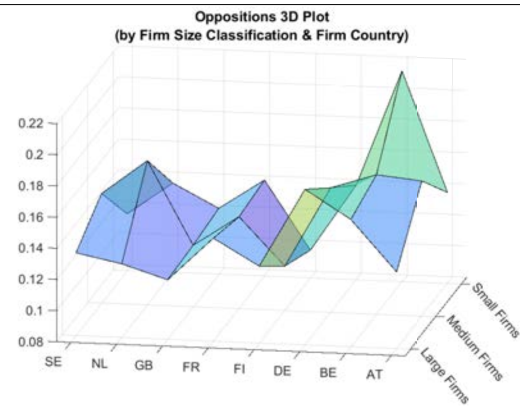
Backward Citations - Pairwise Correlations
[over Technological Sectors]

Variables	(1)	(2)	(3)
(1) Large Firms	1.000		
(2) Medium Firms	0.995*	1.000	
(3) Small Firms	0.988*	0.979*	1.000

6.7 Oppositions - Figures and Tables

6.7.1 Oppositions: Correlation - Firm Size & Firm Country

In order to get more insights regarding potential drivers of these persistent cross-country differences in their opposition rate outcomes, more sophisticated analyses are conducted. Therefore, the subsequent figure depicts the pairwise correlations of opposition rate outcomes between the firm country classification and the firm size classification.



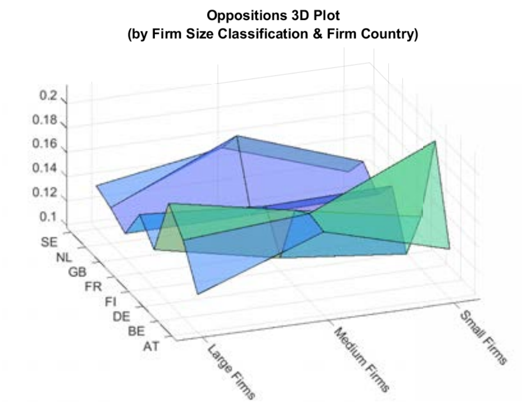
Oppositions - Pairwise Correlations
[over Firm Country]

Variables	(1)	(2)	(3)
(1) Large Firms	1.000		
(2) Medium Firms	0.400	1.000	
(3) Small Firms	0.544	0.628	1.000

It is analyzed whether the firm country opposition rates are correlated over the three firm size classifications. A high pairwise correlation of the opposition outcomes between large and medium-sized firms would imply that large and medium-sized firms are affected similarly regarding their opposition outcomes irrespectively of the countries in which these firms are located in. From the pairwise correlation values of the meaned opposition rate outcomes above, it can be seen that the correlation coefficients are positive, however insignificant between the firm size categories.[59] This suggests that the firms' locations have systematically different impacts on the opposition rates across small, medium-sized and large firms and that the above established differences in firm country opposition rates are not driven by comparable opposition evolvements across firms from different size categories. In the next figure, the perspective is reversed and

[59] A star in the table would indicate significance at the 5 percent level.

the correlations of opposition rates for firms of different sizes across the firm-country locations are depicted. A high pairwise correlation of the meaned opposition rate outcomes between two firm countries would imply that firms from these countries are on average affected similarly in their opposition outcomes over the three firm size classifications. When the outcomes from the correlation matrix below are considered, it can be seen that while the correlation coefficients range from highly positive values to highly negative outcomes



Oppositions - Pairwise Correlations
[over Firm Size Classifications]

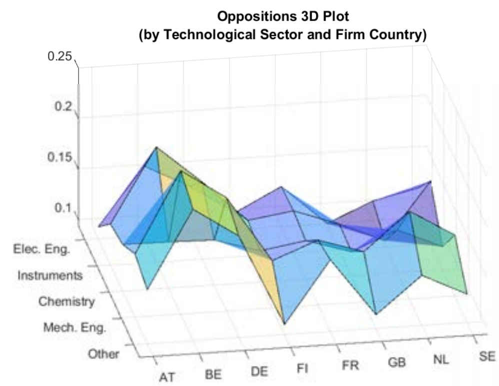
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Austria	1.000							
(2) Belgium	-0.150	1.000						
(3) Germany	-0.247	-0.921	1.000					
(4) Finland	-0.409	-0.841	0.985	1.000				
(5) France	-0.912	-0.270	0.623	0.748	1.000			
(6) Great Brittain	0.018	0.986	-0.973	-0.920	-0.427	1.000		
(7) Netherlands	1.000*	-0.176	-0.221	-0.384	-0.900	-0.009	1.000	
(8) Sweden	0.729	-0.786	0.483	0.326	-0.383	-0.671	0.747	1.000

between the firm countries, there are rarely significant correlations observable. Therefore, these results indicate that the opposition outcomes across firm countries have diverse structures over the three firm size classifications, which implies that firms from different countries are affected differently in their opposition outcomes across small, medium and large firms.

Analogous figures for pairwise correlations between opposition outcomes referring to firm countries and the technological sectors of the patent applications are depicted and attached in subsection 6.7.2 of this paper. From these figures, it can be inferred that the opposition outcomes in the different technological sectors are positively and significantly correlated across firm countries between many technological sectors. Therefore, patents from these sectors are affected similarly in their opposition rates across the firms from different countries. On the other hand, when the perspective is reversed, the opposition rates are positive and for some countries significantly correlated across the different technological sectors as, for instance, firms from France and Germany have highly positive and statistically significant correlation coefficients regarding their opposition rates across the technological sectors considered. Finally, correlation analyses which refer to the firm size classification and the technological sectors are depicted in in the appendix in section 6.7.3 of this paper.

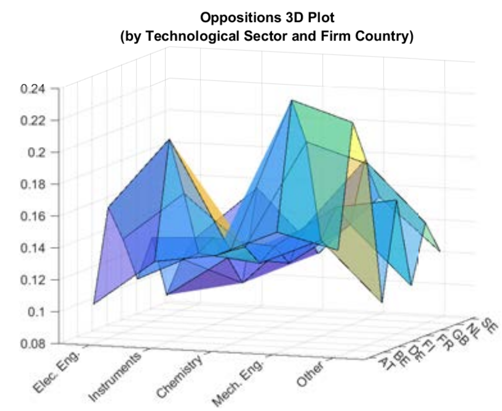
Summarizing, the descriptive analyses regarding the opposition rate evolvements serve as a starting point for further and more sophisticated analyses. More research might provide explanations for the high opposition rates of the patents from the European firms analyzed in this paper as well as for the time persistent differences across firms from different European countries.

6.7.2 Oppositions: Correlation - Firm Country & Technology



Oppositions - Pairwise Correlations
[over Firm Country]

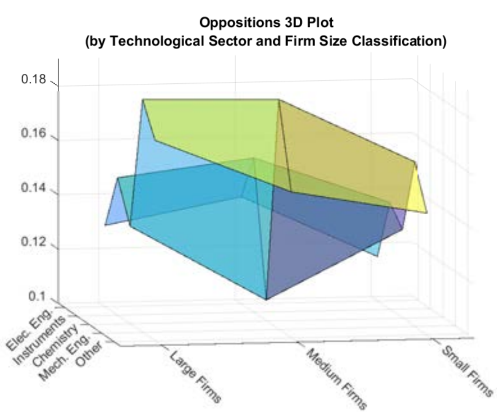
Variables	(1)	(2)	(3)	(4)	(5)
(1) Electr. Eng.	1.000				
(2) Instruments	0.853*	1.000			
(3) Chemistry	0.484	0.288	1.000		
(4) Mech. Eng.	0.848*	0.740*	0.668	1.000	
(5) Other	0.888*	0.756*	0.758*	0.928*	1.000

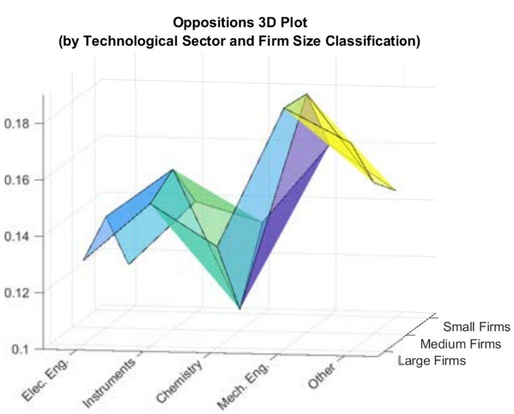


Oppositions - Pairwise Correlations
[over Technological Sectors]

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Austria	1.000							
(2) Belgium	0.598	1.000						
(3) Germany	0.761	0.965*	1.000					
(4) Finland	0.459	0.225	0.271	1.000				
(5) France	0.673	0.818	0.899*	-0.091	1.000			
(6) Great Brittain	0.811	0.512	0.624	0.883*	0.351	1.000		
(7) Netherlands	0.734	0.447	0.644	0.389	0.694	0.687	1.000	
(8) Sweden	0.343	0.659	0.557	0.739	0.145	0.677	0.112	1.000

6.7.3 Oppositions: Correlation - Firm Size & Technological Sector





Oppositions - Pairwise Correlations
[over Firm Size Classifications]

Variables	(1)	(2)	(3)	(4)	(5)
(1) Electr. Eng.	1.000				
(2) Instruments	0.998*	1.000			
(3) Chemistry	-0.743	-0.701	1.000		
(4) Mech. Eng.	0.898	0.923	-0.372	1.000	
(5) Other	0.396	0.451	0.320	0.760	1.000

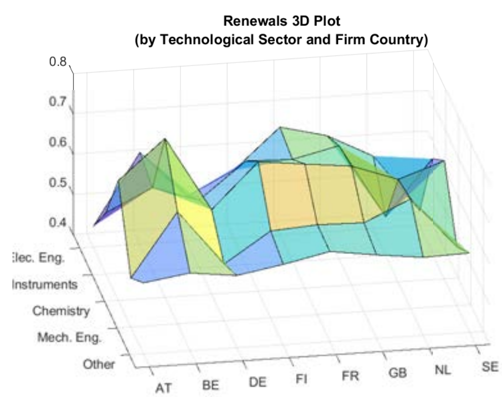
Oppositions - Pairwise Correlations
[over Technological Sectors]

Variables	(1)	(2)	(3)
(1) Large Firms	1.000		
(2) Medium Firms	0.808	1.000	
(3) Small Firms	0.937*	0.704	1.000

6.8 Renewals

6.8.1 Renewals: Correlation - Firm Country & Technological Sector

The following set of analyses utilizes the information on the technological sectors and conducts correlation analyses of the renewal share outcomes conditional on the firm country and firm size classification, respectively. Starting with the firm country classification, it is analyzed whether the firm country renewal rate outcomes are correlated over the technological sector classifications. A high pairwise correlation of the renewal rate outcomes between firms from different technological sectors would imply that firms from these sectors are affected similarly regarding their renewal outcomes irrespectively of the countries in which these firms are located in.[60] From the pairwise correlation values of the meaned renewal rate outcomes below, it can be seen that the correlation coefficients are positive and highly significant between the Electrical and Mechanical Engineering as well as the residual technological sectors. This suggests that patents which are classified into these technological sectors are impacted similarly regarding their patent renewals across firms from different countries.

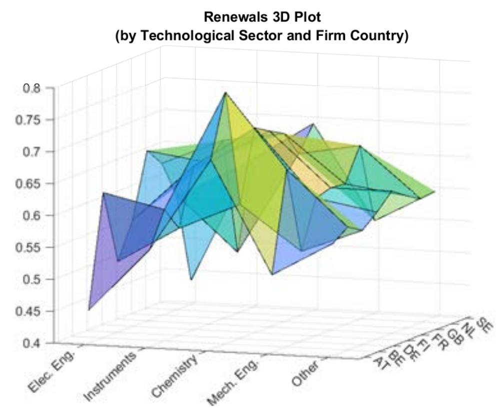


Renewals - Pairwise Correlations
[over Firm Country]

Variables	(1)	(2)	(3)	(4)	(5)
(1) Electr. Eng.	1.000				
(2) Instruments	0.357	1.000			
(3) Chemistry	0.363	0.408	1.000		
(4) Mech. Eng.	0.805*	0.020	0.473	1.000	
(5) Other	0.715*	0.651	0.288	0.477	1.000

In the next figure, the perspective is reversed and the correlations of renewal rates for firms from different countries across the technological sectors of the patents are depicted. A high pairwise correlation of the meaned renewal rate outcomes between two firm countries would imply that firms from these countries are on average affected similarly in their renewal outcomes across the technological sectors of their patents.

[60] A star in the table below would indicate significance at the 5 percent level.



Renewals - Pairwise Correlations
[over Technological Sectors]

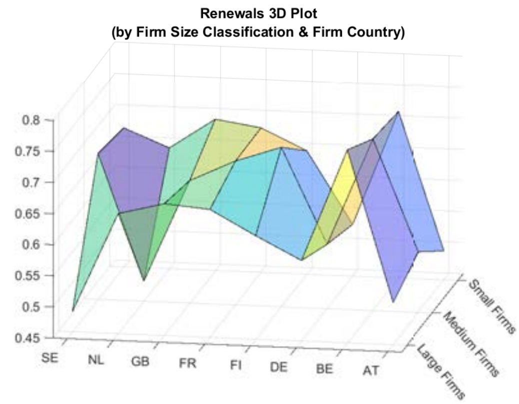
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Austria	1.000							
(2) Belgium	0.699	1.000						
(3) Germany	0.970*	0.508	1.000					
(4) Finland	0.896*	0.753	0.840	1.000				
(5) France	0.525	0.723	0.381	0.650	1.000			
(6) Great Brittain	0.560	0.578	0.490	0.821	0.842	1.000		
(7) Netherlands	0.303	0.673	0.136	0.158	0.076	-0.212	1.000	
(8) Sweden	0.925*	0.481	0.964*	0.899*	0.347	0.588	0.035	1.000

When the outcomes from the correlation matrix above are considered, it can be seen that the correlation coefficients are predominantly positive and statistically significant between firms from countries such as Finland and Austria, as well as between Sweden and Austria, Germany and Finland. This suggests that the renewal rate outcomes across the technological sectors of the patents have similar structures over the firm countries considered, which implies that firms from different countries are affected similarly in their renewal outcomes across these sectors.

Finally, analogous figures for pairwise correlations regarding the renewal rate outcomes that refer to comparative analyses across firm countries and firm size classifications are depicted and attached in subsection 6.8.2 of this paper. From these figures, it can be inferred that the renewal rate outcomes in the different firm size classifications are insignificantly correlated across the firm countries. Therefore, patents from firms with different sizes are affected in rather different manners across the firm countries considered in this paper. When the perspective is reversed, the renewal outcomes are also insignificantly correlated for the firm countries across the different firm size classifications. Besides this, further correlation analyses of the renewal rates across the firm size and technological sector classifications can be found in the appendix of this paper in section 6.8.3. They contain overall insignificant correlation coefficients.

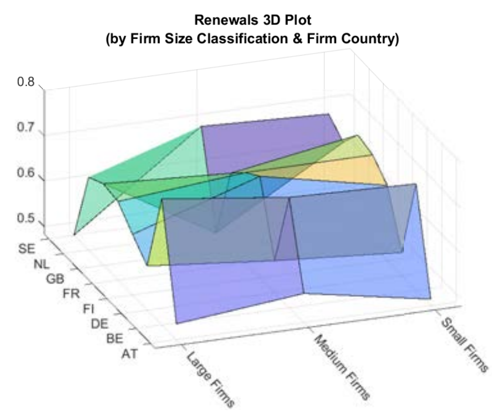
Summing up, the descriptive analyses regarding the renewal rate evolvements show that while there are time persistent and statistically significant differences across the technological sectors considered, these stable differences across time cannot be established across firms with different sizes as well as firms from different countries. However, the correlation analyses suggest that there appear to be persistent and significant similarities in the renewal rate evolvements for firms with different sizes across some technological sectors. Overall, these descriptive findings provide room for future research.

6.8.2 Renewals: Correlation - Firm Country & Firm Size



Renewals - Pairwise Correlations
[over Firm Country]

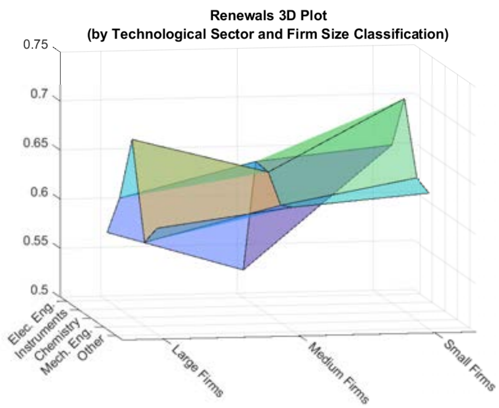
Variables	(1)	(2)	(3)
(1) Large Firms	1.000		
(2) Medium Firms	0.298	1.000	
(3) Small Firms	0.595	0.658	1.000

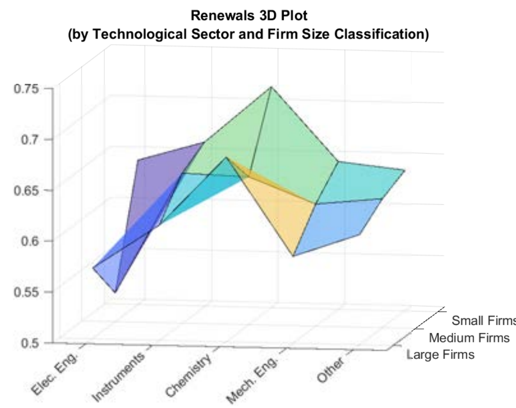


Renewals - Pairwise Correlations
[over Firm Size Classifications]

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Austria	1.000							
(2) Belgium	0.091	1.000						
(3) Germany	0.353	0.964	1.000					
(4) Finland	0.700	-0.648	-0.422	1.000				
(5) France	0.054	-0.989	-0.915	0.752	1.000			
(6) Great Brittain	-0.958	-0.373	-0.606	-0.465	0.234	1.000		
(7) Netherlands	-0.909	0.333	0.070	-0.934	-0.466	0.751	1.000	
(8) Sweden	0.135	-0.974	-0.880	0.802	0.997	0.155	-0.536	1.000

6.8.3 Renewals: Correlation - Firm Size & Technological Sector





Renewals - Pairwise Correlations
[over Firm Size Classifications]

Variables	(1)	(2)	(3)	(4)	(5)
(1) Electr. Eng.	1.000				
(2) Instruments	0.427	1.000			
(3) Chemistry	0.987	0.276	1.000		
(4) Mech. Eng.	0.556	0.989	0.415	1.000	
(5) Other	0.517	0.995	0.372	0.999*	1.000

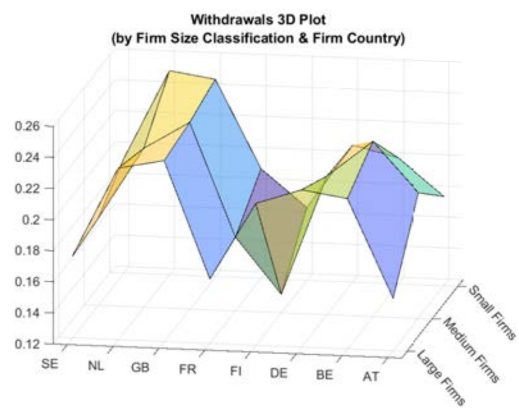
Renewals - Pairwise Correlations
[over Technological Sectors]

Variables	(1)	(2)	(3)
(1) Large Firms	1.000		
(2) Medium Firms	0.670	1.000	
(3) Small Firms	0.928*	0.467	1.000

6.9 Withdrawals - Figures and Tables

6.9.1 Withdrawals: Correlation - Firm Size & Firm Country

In order to get more insights regarding potential drivers of these persistent cross-country differences in firms' patent withdrawal rates, the figure below depicts the pairwise correlations of withdrawal rate outcomes between firm countries and firm sizes. More precisely, it is analyzed whether



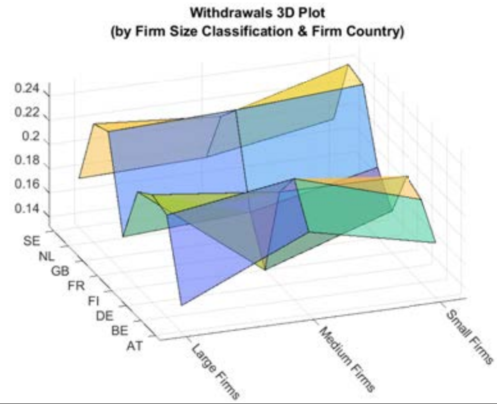
Withdrawals - Pairwise Correlations
[over Firm Country]

Variables	(1)	(2)	(3)
(1) Large Firms	1.000		
(2) Medium Firms	0.476	1.000	
(3) Small Firms	0.670	0.757*	1.000

the firm country withdrawal rates are correlated over the three firm size classifications which were found to be characterized by no time-persistent and systematic differences in their withdrawal rates based on the previous analyses from above. A high pairwise correlation of the withdrawal outcomes between large and medium-sized firms would imply that large and medium-sized firms are affected similarly regarding their withdrawal outcomes irrespectively of the countries in which these firms are located in. From the pairwise correlation values of the meaned withdrawal rate outcomes above, it can be seen that the correlation between the withdrawal rate outcomes of small and medium sized firms is positive and statistically significant across the different countries considered. Besides this, no significant correlation towards the withdrawal outcomes of large firms can be established.[61] This descriptive finding suggests that firms' locations have systematically similar impacts on withdrawal rates of small and medium firms while large firms are affected differently across the firm countries.

In the next figure, the perspective is reversed and the correlations of the withdrawal rate outcomes for firms of different sizes are depicted across different firm-country locations. A high pairwise correlation of

[61] A star in the table would indicate significance at the 5 percent level.



Withdrawals - Pairwise Correlations
[over Firm Size Classifications]

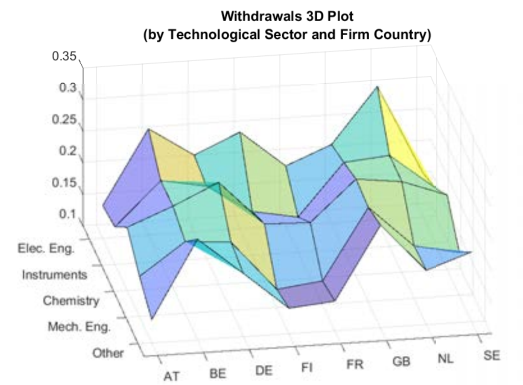
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Austria	1.000							
(2) Belgium	0.502	1.000						
(3) Germany	-0.825	0.075	1.000					
(4) Finland	-0.99*	-0.444	0.860	1.000				
(5) France	0.201	-0.747	-0.719	-0.264	1.000			
(6) Great Brittain	0.341	-0.642	-0.813	-0.401	0.989	1.000		
(7) Netherlands	-0.267	-0.968	-0.324	0.204	0.890	0.815	1.000	
(8) Sweden	0.151	-0.780	-0.683	-0.215	0.999*	0.981	0.912	1.000

the meaned withdrawal rate outcomes between two firm countries would imply that firms from these countries are on average affected similarly in their withdrawal rates over the three firm size classifications. When the outcomes from the correlation matrix above are considered, it can be seen that the correlation coefficients range from highly negative to highly positive values across different countries, while most of them are statistically insignificant. The only exceptions are Finland and Austria as well as Sweden and France which are both depicted by highly positive and significant correlations. Apart from these cases, the overall correlation results suggest that firms from different countries are impacted systematically differently in their withdrawal rates across small, medium-sized and large firms. Therefore, the above established differences in withdrawal rates between the firm countries may be potentially explained by these differences across the different firm size categories.

Finally, analogous correlation figures of withdrawal rate outcomes which refer to firm countries and the technological sectors of the patent applications are depicted and attached in subsection 6.9.2 of this paper. It can be inferred from these figures that the withdrawal rates of patents from different technological sectors are positively and significantly correlated across the patenting firms from different countries. Therefore, patent withdrawals attributed to these technological sectors are affected similarly across firms from the respective countries. When the perspective is reversed, the withdrawal rates are positive and for some countries significantly correlated across the different technological sectors. For instance, firms from Germany and Austria have highly positive and statistically significant correlation coefficients regarding their withdrawal rate outcomes across the different technological sectors considered. Finally, correlation analyses which refer to the firm size classification and the technological sectors are depicted in in the appendix in section 6.9.3 of this paper.

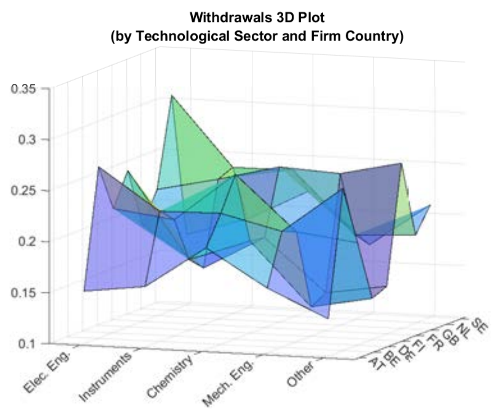
In conclusion, the descriptive analyses regarding the withdrawal rate evolvements show that while there are time persistent and statistically significant differences across the technological sectors as well as regarding the firm countries considered, such systematic differences across time cannot be established across small, medium and large firms. The correlation analyses suggest that the cross-country differences in the withdrawal outcomes are potentially driven by differences in firms' withdrawal behavior across firms with different sizes and applications from different technological sectors. These descriptive findings provide room for more sophisticated follow-up analyses.

6.9.2 Withdrawals: Correlation - Firm Country & Technology



Withdrawals - Pairwise Correlations
[over Firm Country]

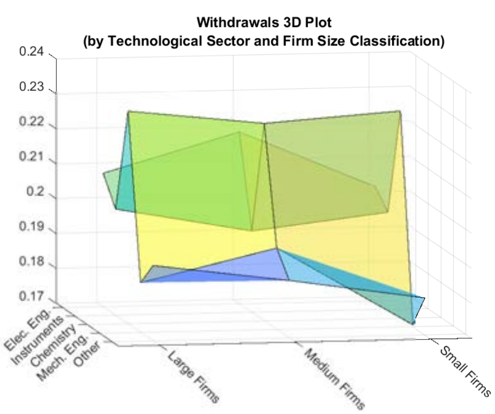
Variables	(1)	(2)	(3)	(4)	(5)
(1) Electr. Eng.	1.000				
(2) Instruments	0.682	1.000			
(3) Chemistry	0.379	0.877*	1.000		
(4) Mech. Eng.	0.219	0.819*	0.864*	1.000	
(5) Other	0.281	0.790*	0.709*	0.882*	1.000

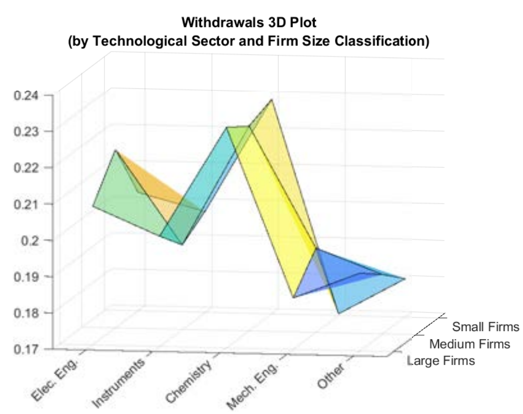


Withdrawals - Pairwise Correlations
[over Technological Sectors]

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Austria	1.000							
(2) Belgium	-0.563	1.000						
(3) Germany	0.915*	-0.188	1.000					
(4) Finland	0.129	0.582	0.432	1.000				
(5) France	0.424	0.451	0.721	0.925*	1.000			
(6) Great Brittain	0.062	-0.256	-0.050	-0.777	-0.535	1.000		
(7) Netherlands	0.136	0.486	0.404	0.980*	0.879*	-0.856	1.000	
(8) Sweden	0.335	0.043	0.449	-0.197	0.118	0.688	-0.257	1.000

6.9.3 Withdrawals: Correlation - Firm Size & Technological Sector





Withdrawals - Pairwise Correlations
[over Firm Size Classifications]

Variables	(1)	(2)	(3)	(4)	(5)
(1) Electr. Eng.	1.000				
(2) Instruments	-0.766	1.000			
(3) Chemistry	-0.760	1.000*	1.000		
(4) Mech. Eng.	0.954	-0.537	-0.529	1.000	
(5) Other	0.363	0.321	0.330	0.626	1.000

Withdrawals - Pairwise Correlations
[over Technological Sectors]

Variables	(1)	(2)	(3)
(1) Large Firms	1.000		
(2) Medium Firms	0.885*	1.000	
(3) Small Firms	0.992*	0.852	1.000

7 Appendix 2 - SQL Commands

The following section discusses the generating process of the patent measures which are presented and analyzed in this paper. As previously discussed, the measures in the paper at hand are generated for the set of those patent applications from European firms which are obtained based on the matching algorithm provided by Peruzzi et al. (2014). This dataset constitutes inter alia the basis of the research project *Financing Innovation in Europe* which was funded by the EPO Academic Research Programme 2017. The paper at hand constitutes one element of this cumulative research project. The documentation of the SQL commands for the respective patent measures is, however, in general independent of the chosen subset of patent applications. Therefore, the provided coding of the patent measures may also contain valuable information for researchers interested in generating patent measures for other subsets of patentees from the Patstat universe. The description of the generating process of each patent measure must account for the fact that the measures i) may be based on information from different Patstat product lines, ii) refer to an individual patent vs. refer to the relation of patents towards each other and iii) may be generated with different software tools more or less efficiently. Therefore, this report aims at giving a detailed overview on these particularities.

Based on the above-mentioned algorithm from Peruzzi et al. (2014), it is possible to match firm-level financials from Bureau van Dijk's Amadeus database with individual patent information from Patstat. This regression-based matching is a precondition to combine patent information with firm-level financials because the respective databases do not share a common, unique identifier which would enable a direct link between these datasets. The resulting matching table links Bureau van Dijk's firm identifier (bvd_id) with person ids from Patstat ($person\_id$). Based on this linkage, the person ids from the matching table constitute the natural starting point for the generating process of the patent measures from Patstat.

Patstat Biblio and Patstat Legal Status are multi-layered databases which consist of multiple tables, each containing information on specific patent related topics. All of them refer directly or indirectly to the TLS201_Appln table (see Figure 0.2 above). According to Chapter 5.1 of the 2017 EPO Biblio and Legal Data Catalog, TLS201_Appln contains the key bibliographical data elements relevant to identify a patent application. This table is of essential importance from a database structure point of view because it is the linking element to other database tables. Therefore, TLS201_APPLN can be considered as the core of Patstat Biblio and Patstat Legal. The primary key of this table is the so called application identifier (appln_id). Relating to Chapter 6.9 of the EPO Biblio and Legal Data Catalog, the appln_id is a technical unique identifier for a combination of application authority, application number and application kind which remains the same across Patstat editions.

7.1 SQL Command 1
Linking application ids to person ids

In order to generate the patent measures for the person ids from the above matching table, in a first step the person ids from this table need to be linked to associated application ids from Patstat. For this purpose, the TLS207_Pers_Appln table is utilized as it contains the required link between the person id and the appln id. Notably, one person id may contain numerous appln ids, as one (natural or legal) person may file many applications. In order to link the application ids to corresponding person ids, in a first step the following command - which inter alia also contains information on the applicants' addresses and the countries of their location - is processed via SQL:

```
SELECT  a.person_id, a.person_id_peruzzi, a.person_address,
        a.person_ctry_code, a.bvdid, a.IDMaster, a.IDMaster_han,
        a.han_id, a.han_name, a.han_harmonized, a.nuts,
        b.appln_id
        INTO INDICATOR_TABLE_Unique_Appln_IDs
        FROM [INDICATOR_TABLE_Add_Person_ID] a
                LEFT JOIN
                (SELECT *
                 FROM dbo.tls207_part01
                 UNION ALL
                 SELECT *
                 FROM dbo.tls207_part02
                 UNION ALL
                 SELECT *
                 FROM dbo.tls207_part03) b
                 ON a.person_id=b.person_id
```

The generated table from this command is called "*Indicator_ Table_ Unique_ Appln_ IDs*". It contains the relevant person ids, i.e. those which are linked to the associated financial data from Amadeus as well as the corresponding application ids. As noted in the paper, one person id may contain numerous application ids. Therefore, as can be seen from above, a "left join" command is conducted, which allows for multiple matches between the table *"Indicator_ Table_ Add_ Person_ ID"* (which contains the unique person ids from the Peruzzi matching table) and the TLS207_Pers_Appln table (which contains the link between person ids and application ids). The above command expands the initial indicator table by the number of patent applications which are attributed to each person id.

In order to ensure that the above joining procedure did not create (person_id-bvd_id)-to-(appln_id) duplicates, the subsequent SQL codes aims at cleaning the *"Indicator_ Table_ Unique_ Appln_ IDs"* from redundant duplicates:

```
ALTER   TABLE INDICATOR_TABLE_Unique_Appln_IDs
ADD     appln_person_bvdid_duplicates int

UPDATE  INDICATOR_TABLE_Unique_Appln_IDs
SET     appln_person_bvdid_duplicates=
        b.appln_person_bvdid_duplicates
FROM    [INDICATOR_TABLE_Unique_Appln_IDs] a
INNER JOIN
        (SELECT appln_id, person_id, bvdid,
         count(appln_id) as 'appln_person_bvdid_duplicates'
         FROM INDICATOR_TABLE_Unique_Appln_IDs
         GROUP BY appln_id, person_id, bvdid) b
        ON a.appln_id=b.appln_id



ALTER   TABLE INDICATOR_TABLE_Unique_Appln_IDs
ADD     countvar int IDENTITY(1,1)
        SELECT  * from  INDICATOR_TABLE_Unique_Appln_IDs
        WHERE   appln_person_bvdid_duplicates>1
        ORDER   BY appln_id, person_id, bvdid

ALTER   TABLE INDICATOR_TABLE_Unique_Appln_IDs
add     ind int

UPDATE  INDICATOR_TABLE_Unique_Appln_IDs
SET     ind=b.ind
FROM    [INDICATOR_TABLE_Unique_Appln_IDs] a
INNER JOIN      (SELECT countvar, appln_id, person_id,
                bvdid, ROW_NUMBER()
                OVER(PARTITION BY appln_id, person_id,
                bvdid ORDER BY countvar) as 'ind'
                FROM INDICATOR_TABLE_Unique_Appln_IDs) b
                ON a.countvar=b.countvar

DELETE  FROM INDICATOR_TABLE_Unique_Appln_IDs
WHERE   ind>1

ALTER   TABLE INDICATOR_TABLE_Unique_Appln_IDs
DROP    COLUMN  appln_person_bvdid_duplicates, countvar, ind
```

7.2 SQL Command 2
Add data from the Patstat TLS201_Appln table

Based on this set of unique application ids, in a next step selected raw data from Patstat table TLS201_-Appln are imported into the current version of the Indicator Table. These data are useful for the generating process of the derived patent measures in the subsequent steps and adjoined to the current indicator table by the following command:

```
SELECT  a.person_id, a.person_id_peruzzi, a.bvdid,
        a.IDMaster, a.IDMaster_han, a.han_id, a.appln_id,
        b.appln_nr, b.appln_auth, b.appln_kind,
        b.appln_filing_date, b.earliest_publn_date,
        b.earliest_pat_publn_id, b.granted, b.ipr_type,
INTO    INDICATOR_TABLE_Unique_Appln_IDs_201
FROM    [INDICATOR_TABLE_Unique_Appln_IDs] a
LEFT JOIN [tls201_COMPLETE] b on a.appln_id=b.appln_id
```

The resulting *"Indicator_ Table_ Unique_ Appln_ IDs_ 201"* from the above command contains the core raw data from the TLS201_Appln table for all individual patent applications from the *"Indicator_ Table_-Unique_ Appln_ IDs"* table. In order to ensure that no person_id-bvd_id-to-appln_id duplicates were generated through this joining procedure, the following SQL command is executed:

```
ALTER TABLE INDICATOR_TABLE_Unique_Appln_IDs_201
ADD     appln_person_bvdid_duplicates int

UPDATE  INDICATOR_TABLE_Unique_Appln_IDs_201
SET     appln_person_bvdid_duplicates=
        b.appln_person_bvdid_duplicates


FROM    [INDICATOR_TABLE_Unique_Appln_IDs_201] a
INNER JOIN
        (SELECT appln_id, person_id, bvdid,
        count(appln_id) as 'appln_person_bvdid_duplicates'
        FROM INDICATOR_TABLE_Unique_Appln_IDs_201
        GROUP BY appln_id, person_id, bvdid) b
        ON a.appln_id=b.appln_id

ALTER   TABLE INDICATOR_TABLE_Unique_Appln_IDs_201
ADD     countvar int IDENTITY(1,1)

ALTER   TABLE INDICATOR_TABLE_Unique_Appln_IDs_201
ADD     ind int

UPDATE  INDICATOR_TABLE_Unique_Appln_IDs_201
SET     ind=b.ind
FROM    [INDICATOR_TABLE_Unique_Appln_IDs_201] a

INNER JOIN
        (SELECT countvar, appln_id, person_id, bvdid,
        ROW_NUMBER() OVER(PARTITION BY appln_id,
        person_id, bvdid ORDER BY countvar) as 'ind'
        FROM INDICATOR_TABLE_Unique_Appln_IDs_201) b
        ON a.countvar=b.countvar

DELETE  FROM INDICATOR_TABLE_Unique_Appln_IDs_201
WHERE   ind>1

ALTER   TABLE INDICATOR_TABLE_Unique_Appln_IDs_201
DROP    COLUMN  appln_person_bvdid_duplicates, countvar, ind
```

Notably, the process of deleting duplicates from the *"Indicator_ Table_ Unique_ Appln_ IDs_ 201"* table leaves the same amount of observations as the *"Indicator_ Table_ Unique_ Appln_ IDs"*. Therefore, appending the essential information from TLS201_Appln leaves the total number of data rows unaffected. This appears reasonable as the core Patstat dataset TLS201_Appln contains in general one unique observation per application id.

7.3 SQL Command 3
Create Final Indicator Table and add Grant Indicator Variable

As it is the final aim of this paper to build an indicator table with patent measures which contains exactly one observation per application id and patent measure, in a next step some variables from the *Indicator_-Table_ Unique_ Appln_ IDs_ 201* are imported into a final version of the Indicator Table, which is referred to as the *Indicator_ Table_ Final_ Measures* or as the *Final Indicator Table* in the remainder of this paper (see also *SQL Command 4*). This final version of the indicator table will be updated with more patent measures in the subsequent sections of this paper - such as the *application filing date* and the *granted* indicator from the TLS201_Appln table:

```
SELECT   *
INTO     INDICATOR_TABLE_FINAL_MEASURES
FROM     INDICATOR_TABLE_Unique_Appln_IDs

ALTER    TABLE INDICATOR_TABLE_FINAL_MEASURES
ADD      appln_filing_date varchar(50)

ALTER    TABLE INDICATOR_TABLE_FINAL_MEASURES
ADD      granted varchar(50)

UPDATE   INDICATOR_TABLE_FINAL_MEASURES
SET      appln_filing_date =     b.appln_filing_date,
         granted           =     b.granted,
FROM     [INDICATOR_TABLE_FINAL_MEASURES] i
INNER JOIN
[INDICATOR_TABLE_Unique_Appln_IDs_201] b
ON       i.appln_id = b.appln_id
```

As can be seen from above, in addition to the final version of the indicator table, further intermediate versions of different indicator tables are also generated (e.g. *"Indicator_ Table_ Unique_ Appln_ IDs_ 201"* vs *"Indicator_ Table_ Final_ Measures"*). These intermediate indicator tables contain all information for the pre-defined set of application ids which are needed in order to generate the respective patent measures from the different Patstat tables. Therefore, the intermediate indicator tables extract the relevant information from the respective Patstat tables into separate, self-generated tables. In order to generate the patent measures in a clear and time efficient way, the patent measures from the intermediate indicator tables will serve as the basis to generate the patent measures for the final indicator table, which contains one single entry per patent measure and application id. Following these considerations, the generating process of the patent measures in the following SQL commands is partly based on intermediate indicator tables which link the relevant application ids with the required information from the respective Patstat tables in order to generate each patent measure. In a subsequent step, the derived data from the intermediate indicator tables are transformed and imported into the final indicator table.

7.4 SQL Command 4
Extract Information on Claims and Grant Publications

In a next step, an intermediate indicator table containing essential data from the TLS211_Pat_Publn table is generated. According to Chapter 5.10 of the 2017 EPO Biblio and Legal Status Data Catalog, this table can be directly linked via the application id. It contains information on two important dimensions which are valuable for the patent measures of this paper, namely i) whether a particular publication can be considered as an indication for a patent grant and ii) the number of claims included in a patent application.

```
SELECT a.person_id, a.bvdid, a.IDMaster, a.IDMaster_han,
       a.han_id, a.appln_id, a.appln_nr, a.appln_auth,
       a.appln_kind, a.appln_filing_date, a.granted, a.ipr_type,
       b.pat_publn_id, b.publn_first_grant, b.publn_claims,
       b.publn_date, b.publn_kind, b.publn_auth
INTO   INDICATOR_TABLE_Unique_Appln_IDs_201_211
FROM   [INDICATOR_TABLE_Unique_Appln_IDs_201] a
LEFT JOIN [tls211_COMPLETE] b
ON a.appln_id=b.appln_id
```

As stated in Chapter 5.10 of the 2017 EPO Biblio and Legal Status Data Catalog, the number of claims is only available for a number of publishing authorities. The variables are processed via SQL into the intermediate indicator table. The command above follows an analogous rationale as compared to the previous commands The *left join* option relationg to the TLS211_Pat_Publn table may generate reasonable duplicates as one application id in the TLS211_Pat_Publn dataset may be included numerous times, because multiple publications might have occurred for this patent application over time.

7.5 SQL Command 5
Generate Grant Lag Measure

The following SQL command contains the documentation of the generating process which relates to the grant lag variable. It measures the time frame in days between the filing date of a patent application and the earliest publication date given that this publication refers to a patent grant. In order to generate this measure, the variables *appln_filing_date* from the TLS201_appln table as well as the *publn_date* and the *publn_first_grant* variables from the TLS211_Pat_Publn table are utilized. Afterwards, the time frame between these two dates is calculated only for those applications for which the publication first grant variable equals 1. In order to ensure that the time frame is only calculated for actual dates, some test variables are implemented in the generating procedure. Particularly, it has to be taken into account that the default values for the application filing date as well as the earliest publication date are *9999-12-31* when no information are available for the respective variable. Furthermore, in very few cases either the application filing date or the earliest publication date are not shown in the date format *YYYY-MM-DD* and exhibit values which cannot be interpreted as dates. In order to calculate the grant lag only for those applications with contain (reasonable) information regarding the dating variables, self-generated test variables are used in order to account for the above-described particularities. The resulting SQL command for these test variables is depicted below:

```sql
ALTER TABLE INDICATOR_TABLE_Unique_Appln_IDs_201_211
ADD      publn_date_testvar1 varchar(50)

ALTER TABLE INDICATOR_TABLE_Unique_Appln_IDs_201_211
ADD      publn_date_testvar2 varchar(50)

ALTER TABLE INDICATOR_TABLE_Unique_Appln_IDs_201_211
ADD      appln_filing_date_testvar1 varchar(50)

ALTER TABLE INDICATOR_TABLE_Unique_Appln_IDs_201_211
ADD      appln_filing_date_testvar2 varchar(50)

ALTER TABLE INDICATOR_TABLE_Unique_Appln_IDs_201_211
ADD      grant_lag varchar(50)

UPDATE [INDICATOR_TABLE_Unique_Appln_IDs_201_211]
SET      publn_date_testvar1 =
         CHARINDEX('-', publn_date)

UPDATE [INDICATOR_TABLE_Unique_Appln_IDs_201_211]
SET      publn_date_testvar2 =
          CHARINDEX('9999', publn_date)
UPDATE [INDICATOR_TABLE_Unique_Appln_IDs_201_211]
SET      appln_filing_date_testvar1 =
         CHARINDEX('-', appln_filing_date)

UPDATE [INDICATOR_TABLE_Unique_Appln_IDs_201_211]
SET      appln_filing_date_testvar2 =
         CHARINDEX('9999', appln_filing_date)
```

The above test variables can be summarized as follows: the two testvar1-variables aim to capture values which are not represented in the standard date format used by the Patstat database, i.e. the *YYYY-MM-DD* format. Utilizing the *charindex* command in SQL, this syntax looks for the first occurrence of the delimiting symbol "-" in each string of the two relevant date variables. Therefore, the correct outcome for this variable in order to classify an input as having a date format would be *5*, because this is the first time (from left to the right) that the "-" sign occurs in the above described dating format. The two testvar2-variables take into account that the default value for applications, for which no date information is provided, is *9999-31-12*. This input has the standard date format and is therefore not captured by the testvar1-variable. In order to exclude entries with this input from the grant-lag calculation, the testvar2 commands look for the first occurrence of the "9999" string in each entry of a date. If a date had the format *9999-31-12*, the output of the charindex-command would be *1*. Therefore, for the generating process of the grant lag variable only those date inputs shall be used for which the testvar1-variables are equal to *5* and for which the testvar2-variables are equal to *zero*. Based on these considerations, the resulting SQL command for the grant lag variable is depicted below:

```
ALTER TABLE INDICATOR_TABLE_Unique_Appln_IDs_201_211
ADD     grant_lag varchar(50)

UPDATE  [INDICATOR_TABLE_Unique_Appln_IDs_201_211]
SET     grant_lag = DATEDIFF(day, appln_filing_date, publn_date)
WHERE   publn_date_testvar1             =5
AND     publn_date_testvar2             =0
AND     appln_filing_date_testvar1      =5
AND     appln_filing_date_testvar2      =0
AND     publn_first_grant               =1
```

This variable generates a clean measure for the grant lag variable. As can be seen from the above code, the patent measure is generated in the intermediate version of the indicator table which contains core data from the TLS201_Appln and the TLS211_Pat_Publn table. As previously described, this indicator table contains duplications with respect to individual patent applications, i.e. more row entries per patent application. Therefore, in a final step the generated grant lag values are imported in the Final Indicator Table on patent application level by the following SQL command:

```
ALTER   TABLE INDICATOR_TABLE_Unique_Appln_IDs_201_211
ADD     grant_lag_appln_mean int

UPDATE  INDICATOR_TABLE_Unique_Appln_IDs_201_211
SET     grant_lag_appln_mean    =       b.grant_lag_appln_mean
FROM    [INDICATOR_TABLE_Unique_Appln_IDs_201_211] i


INNER JOIN
        (SELECT appln_id, AVG(CAST(grant_lag as INT))
        as 'grant_lag_appln_mean'
        FROM    INDICATOR_TABLE_Unique_Appln_IDs_201_211
        GROUP BY appln_id) b
ON      i.appln_id = b.appln_id

SELECT  * FROM INDICATOR_TABLE_FINAL_MEASURES
ALTER   TABLE INDICATOR_TABLE_FINAL_MEASURES
ADD     grant_lag varchar(50)

UPDATE  INDICATOR_TABLE_FINAL_MEASURES
SET     grant_lag = b.grant_lag_appln_mean
FROM    [INDICATOR_TABLE_FINAL_MEASURES] i
INNER JOIN [INDICATOR_TABLE_Unique_Appln_IDs_201_211] b
ON      i.appln_id = b.appln_id
```

While almost all patent applications contain information regarding publication dates as well as filing dates, only a subset of patent applications contain the information that a publication was the first indication for a patent grant. However, many patent applications contain information as to whether the patent application was granted or not as can be seen from the "granted" variable which was also imported into the intermediate Indicator table in the previous subsection 7.4. In order to see how the granted variable and the publication first grant variable relate to each other, additional tests are executed, based on which it can be ascertained that all patent applications for which the publication first grant variable is equal to 1 are also classified as granted patents. Furthermore, as described in Chapter 6.69 of the EPO Biblio and Legal Data Catalog, the granted variable is derived from the publication first grant variable. However, only a subset of the patent applications included in Patstat contain information on the publication first grant variable. Relating to this issue, it is said in the comments to Chapter 6.69 of the 2017 EPO Biblio and Legal Data Catalog that some offices do not always publish granted patents but just issue a legal event. Therefore, the indication of a granted patent in the absence of a corresponding publication of a grant does not constitute a contradiction per se. For example, the event code "FG" from the Patstat Legal Database indicates that a patent was granted even though there was no specific publication of the grant and therefore the granted variable might be zero. Furthermore, as described in Chapter 6.69 of the EPO Biblio and Legal Data Catalog regarding the publication first grant variable, it is said that the generating process for this variable is a result of interpretations and assumptions for which no responsibility can be accepted.

7.6 SQL Command 6 Generate Patent Claims Measure

Based on the considerations from subsection 7.4, the intermediate indicator table which is processed by SQL command 4 contains information on the number of claims included in the patent applications. Based on the above described specificities of this indicator table, in a final step, the generated claim outcomes of these patent applications are added to the Final Indicator Table by processing the following SQL command on patent application level:

```
ALTER   TABLE INDICATOR_TABLE_Unique_Appln_IDs_201_211
ADD     publn_claims_appln_mean int
UPDATE  INDICATOR_TABLE_Unique_Appln_IDs_201_211
SET     publn_claims_appln_mean         =
        b.publn_claims_appln_mean

FROM    [INDICATOR_TABLE_Unique_Appln_IDs_201_211] i
INNER JOIN
(SELECT appln_id, AVG(CAST(publn_claims as INT))
        as 'publn_claims_appln_mean'
FROM    INDICATOR_TABLE_Unique_Appln_IDs_201_211
GROUP BY appln_id) b
ON      i.appln_id = b.appln_id

UPDATE  INDICATOR_TABLE_FINAL_MEASURES
SET     publn_claims = b.publn_claims_appln_mean
FROM    [INDICATOR_TABLE_FINAL_MEASURES] i
INNER JOIN [INDICATOR_TABLE_Unique_Appln_IDs_201_211] b
ON      i.appln_id = b.appln_id
```

7.7 SQL Command 7 Generate Patent Scope Measure

The following SQL command describes the generating process of the patent scope measure based on the IPC4 classification. In order to calculate this measure, the first 4 digits of the IPC classification are counted per patent application. In order to generate this count variable based on the above-described structure of the IPC from section 4.3 of this paper, in a first step the information from the TLS209_Appln_Ipc table are added to the set unique application ids using the following SQL command:

```
SELECT          a.person_id, a.bvdid, a.IDMaster, a.IDMaster_han,
                a.han_id, a.appln_id, b.ipc_class_symbol,
                b.ipc_class_level, b.ipc_version, b.ipc_value,
                b.ipc_position, b.ipc_gener_auth
INTO            INDICATOR_TABLE_Unique_Appln_IDs_209
FROM            [INDICATOR_TABLE_Unique_Appln_IDs] a
LEFT JOIN       [tls209_COMPLETE] b on a.appln_id=b.appln_id
```

The resulting intermediate indicator table contains information on the IPC classes entailed in each patent application. Distinct IPCs are covered in different rows. Therefore, the indicator table containing information from the TLS209_Appln Ipc entails numerous rows for each patent application, depending on the number of IPCs contained in the respective patent application. Based on this table, in a next step the patent scope measure which is based on the IPC4 classification, is generated using the following SQL code:

```
ALTER TABLE     INDICATOR_TABLE_Unique_Appln_IDs_209
ADD             patent_scope_ipc4 varchar(50)
UPDATE          [INDICATOR_TABLE_Unique_Appln_IDs_209]
SET             patent_scope_ipc4 = t.patent_scope_ipc4
FROM            [INDICATOR_TABLE_Unique_Appln_IDs_209] i
INNER JOIN
(SELECT appln_id, COUNT(distinct LEFT(ipc_class_symbol, 4))
        as 'patent_scope_ipc4'
                FROM [INDICATOR_TABLE_Unique_Appln_IDs_209]
                WHERE ipc_class_symbol LIKE
                '[A-H][0-9][0-9][A-Z]%'
                GROUP BY appln_id) t
ON              i.appln_id = t.appln_id
```

The resulting patent scope IPC4 variable contains duplicates for each application id due to the structure of the newly generated intermediate indicator table which contains the information from the TLS209_Appln_Ipc table. In order to get rid of the duplicate information on the patent scope of individual patent applications, the results need to be imported to the final indicator table in analogy to the proceedings before. Therefore, in order to translate the duplicate values regarding the patent scope measure on individual patent application level to one unique value in the final Indicator Table, the following SQL commands are conducted:

```
ALTER TABLE     INDICATOR_TABLE_FINAL_MEASURES
ADD             patent_scope_IPC4 varchar(50)

UPDATE          [INDICATOR_TABLE_FINAL_MEASURES]
SET             patent_scope_IPC4 = t.patent_scope_IPC4
FROM            [INDICATOR_TABLE_FINAL_MEASURES] i
INNER JOIN      (SELECT appln_id, patent_scope_IPC4
                FROM INDICATOR_TABLE_Unique_Appln_IDs_209) t
ON              i.appln_id = t.appln_id
```

Based on the above coding, the *final indicator table* contains the patent scope IPC 4 values on individual patent application level. In analogy to this procedure, a tighter IPC 8 measure of the patent scope variable can also be derived. This measure additionally takes into account differences on main group level (see WIPO (2018b)). The resulting SQL codes become:

```
ALTER TABLE      INDICATOR_TABLE_Unique_Appln_IDs_209
ADD              patent_scope_ipc8 varchar(50)

UPDATE           [INDICATOR_TABLE_Unique_Appln_IDs_209]
SET              patent_scope_ipc8 = t.patent_scope_ipc8
FROM             [INDICATOR_TABLE_Unique_Appln_IDs_209] i
INNER JOIN
(SELECT          appln_id, COUNT(distinct
                 LEFT(ipc_class_symbol, 8))
                 as 'patent_scope_ipc8'
FROM             [INDICATOR_TABLE_Unique_Appln_IDs_209]
WHERE            ipc_class_symbol LIKE '[A-H][0-9][0-9][A-Z]

[''OR0-9][``OR0-9][``OR0-9][``OR0-9]%'
GROUP BY          appln_id) t
ON               i.appln_id = t.appln_id

ALTER TABLE      INDICATOR_TABLE_FINAL_MEASURES
ADD              patent_scope_ipc8 varchar(50)

UPDATE           [INDICATOR_TABLE_FINAL_MEASURES]
SET              patent_scope_ipc8 = t.patent_scope_ipc8
FROM             [INDICATOR_TABLE_FINAL_MEASURES] i
INNER JOIN       (SELECT appln_id, patent_scope_ipc8
                 FROM INDICATOR_TABLE_Unique_Appln_IDs_209) t
ON               i.appln_id = t.appln_id
```

The resulting size measures of the IPC8 patent scope variable are - per construction - bigger or equal than the IPC4 patent scope variables and contain more variation in their outcomes because they analyze differences in IPC classes also on IPC main group level.

7.8 SQL Command 8 Generate Family Size Measure

In order to generate the geographical patent size measure, data from the TLS211_Pat_Publn table are utilized. This table contains information which can be used to extract information on the patent offices of destination, more precisely the publication authorities of the INPADOC family members. In accordance with de Rassenfosse et al. (2014), one way to generate a geographic measure on the patent family size is to exclude the PCT publication authority (WO) as it has an international coverage. Adding the PCT applications at international phase would inflate the geographical family count by one unit per affected application. Based on these considerations, the SQL code for the geographical family size becomes:

```
ALTER   TABLE INDICATOR_TABLE_FINAL_MEASURES
ADD     geo_family_size varchar(50)

UPDATE  INDICATOR_TABLE_FINAL_MEASURES
SET     geo_family_size = e.geo_family_size
FROM    [INDICATOR_TABLE_FINAL_MEASURES] i
INNER JOIN
(
SELECT
 a.appln_id,
 COUNT(DISTINCT d.publn_auth) AS geo_family_size
FROM INDICATOR_TABLE_FINAL_MEASURES a
INNER JOIN [tls201_COMPLETE] b
ON b.appln_id = a.appln_id
        INNER JOIN [tls201_COMPLETE] c
        ON c.inpadoc_family_id = b.inpadoc_family_id
                INNER JOIN [tls211_COMPLETE] d
                ON d.appln_id = c.appln_id
WHERE d.publn_auth != 'WO'
GROUP BY a.appln_id
) e
ON      i.appln_id = e.appln_id
```

7.9 SQL Command 9
Generate Forward Citations Measure

In order to generate the forward citations patent measure, information from the TLS211_Pat_Publn table as well as from the TLS212_Citations table are utilized. It is important to note that - in order to calculate the forward citations - the whole universe of published patents from the TLS212_Citations table need to be taken into account. Based on the information included in this table, the distinct patent publications which cite a particular published patent need to be counted. In order to achieve this for the set of unique patent applications which are included in the final indicator table, the variable *pat_publn_id* from the TLS211_Pat_Publn table is used and added to the final indicator table. Afterwards - based on the TLS212_Citation table - the cases for which the *pat_publn_id = cited pat publn id*, i.e. those distinct patent publications which cite the respective patent publication need to be found. Based on these considerations, the forward citations for the first five years after publication are generated as follows:[62]

```
SELECT  t1.appln_id, COUNT(distinct t3.pat_publn_id)
AS 'fwd_cits_5yrs'
INTO    INDICATOR_TABLE_fwd_cits_5yrs
FROM
[INDICATOR_TABLE_FINAL_MEASURES] t1

INNER JOIN
(SELECT appln_id, MIN(publn_date) AS 'earliest_date'
FROM     dbo.tls211_COMPLETE
GROUP BY appln_id) t2
ON       t1.appln_id = t2.appln_id
```

[62]In analogy to this coding, the forward citations measure of patent publications can also be calculated for a wider time window, for instance the 7 subsequent years after the publication date of a patent application

```
LEFT JOIN
        (SELECT *
         FROM dbo.tls211_COMPLETE) t2b ON
         t2b.appln_id = t2.appln_id
         LEFT JOIN
         (SELECT *
         FROM   dbo.tls212_COMPLETE) t3
         ON     t2b.pat_publn_id = t3.cited_pat_publn_id
         LEFT JOIN
                (SELECT *
                 FROM   dbo.tls211_COMPLETE) t4
                 ON     t3.pat_publn_id = t4.pat_publn_id
                 WHERE  t2b.publn_auth <> 'NULL'
                 AND    t4.publn_auth <> 'NULL'
                 AND    YEAR(t2.earliest_date)!= 9999
                 AND    YEAR(t4.publn_date)!= 9999
                 AND    DATEDIFF(YEAR, t2.earliest_date,
                 t4.publn_date) <= 5
                 GROUP BY t1.appln_id

ALTER TABLE INDICATOR_TABLE_FINAL_MEASURES
ADD     fwd_cits_5yrs varchar(50)

UPDATE INDICATOR_TABLE_FINAL_MEASURES
SET     fwd_cits_5yrs = b.fwd_cits_5yrs
FROM    [INDICATOR_TABLE_FINAL_MEASURES] i
INNER JOIN [INDICATOR_TABLE_fwd_cits_5yrs] b
ON      i.appln_id = b.appln_id
```

7.10 SQL Command 10
Generate Backward Citations Measure

In this section, the specificities for the generating process of the backward citations patent measure are discussed. For this purpose, information from the TLS212_Citations table are utilized. In this context, it needs to be noted that the primary key of the TLS212_Citation table is the *pat_publn_id*. This variable is already imported into an intermediate indicator table containing the relevant information from the TLS211_Pat_Publn table (see subsection 7.5) which consists of numerous entries of different patent publication ids per unique patent application id. Therefore, in order to add further information from the TLS212_Citation table, the following SQL commands are conducted:

```
SELECT  a.person_id, a.appln_id, a.pat_publn_id, b.citn_id,
        b.citn_origin, b.cited_pat_publn_id, b.cited_appln_id,
        b.pat_citn_seq_nr, b.cited_npl_publn_id,
        b.npl_citn_seq_nr, b.citn_gener_auth
INTO            INDICATOR_TABLE_Unique_Appln_IDs_211_212
FROM            [INDICATOR_TABLE_Unique_Appln_IDs_201_211] a
                LEFT JOIN
                [tls212_COMPLETE] b on
                a. pat_publn_id=b.pat_publn_id
```

The resulting intermediate indicator table contains information with numerous entries per pat_publn_id on individual patent application id level. In order to generate the total backward citations measure based on this intermediate indicator table, the following SQL commands, which finally add the backward citation outcomes on application level to the final indicator table, are executed:

```
ALTER TABLE INDICATOR_TABLE_Unique_Appln_IDs_211_212
ADD     bwd_cits_total varchar(50)

UPDATE INDICATOR_TABLE_Unique_Appln_IDs_211_212
SET     bwd_cits_total = t.bwd_cits_total
FROM    [INDICATOR_TABLE_Unique_Appln_IDs_211_212] i
INNER JOIN
        (SELECT pat_publn_id, MAX(cast(citn_id as int))
        as 'bwd_cits_total'
        FROM INDICATOR_TABLE_Unique_Appln_IDs_211_212
        GROUP BY pat_publn_id) t
        ON i.pat_publn_id = t.pat_publn_id

ALTER TABLE INDICATOR_TABLE_Unique_Appln_IDs_211_212
ADD     bwd_cits_total_appln_mean int

UPDATE  INDICATOR_TABLE_Unique_Appln_IDs_211_212
SET     bwd_cits_total_appln_mean =
        b.bwd_cits_total_appln_mean
FROM    [INDICATOR_TABLE_Unique_Appln_IDs_211_212] i
INNER JOIN
        (SELECT pat_publn_id, appln_id,
        AVG(CAST(bwd_cits_total as INT))
        as 'bwd_cits_total_appln_mean'
        FROM    INDICATOR_TABLE_Unique_Appln_IDs_211_212
        GROUP BY pat_publn_id, appln_id) b
        ON      i.appln_id = b.appln_id

ALTER   TABLE INDICATOR_TABLE_FINAL_MEASURES
ADD     bwd_cits_total varchar(50)

UPDATE  INDICATOR_TABLE_FINAL_MEASURES
SET     bwd_cits_total =
        b.bwd_cits_total_appln_mean
FROM    [INDICATOR_TABLE_FINAL_MEASURES] i
INNER JOIN
        [INDICATOR_TABLE_Unique_Appln_IDs_211_212] b
        ON      i.appln_id = b.appln_id
```

7.11 SQL Command 11 Generate Measures from Patstat Legal Status

In a next step, patent measures derived from the Patstat Legal database are generated. These measures are based on the TLS231_Inpadoc_Legal_Event table. According to Chapter 5.23 of the EPO Biblio and Legal Data Catalog, this table contains information on legal events which occurred during the life of a patent, either before or after grant. These events include also information on patent oppositions, patent renewals and patent withdrawals which are discussed in detail in sections 4.1 to 4.3 of this paper. Stata coding is utilized in order to translate the information on the event code which are contained in the TLS231_Inpadoc_Legal_Event table into the corresponding indicator variables which indicate whether a patent has been opposed or withdrawn. For this purpose, additional information on the *Categorization of recently used legal status codes*, which are provided by the EPO, are utilized.[63] Afterwards, the intermediate indicator table *Indicator Table unique Appln IDs 201 231 event* is generated. It needs to be noted that

[63] see *https://www.epo.org/searching-for-patents/data/coverage/regular.html*

one patent application may contain numerous entries per legal event. Therefore, the dimensionality of this intermediate indicator table is bigger than of the final indicator table which contains one row per application id. Based on these considerations, some SQL transformations are performed regarding the preliminary indicator table in order to finally add the derived information on the legal events to the final indicator table. These transformations translate the multi-dimensional information regarding individual patent applications into single values per individual patent application id:

```
UPDATE   INDICATOR_TABLE_Unique_Appln_IDs_201_231event
SET      withdr_total =  b.withdr_total,
         oppos_total  =  b.oppos_total

FROM     [INDICATOR_TABLE_Unique_Appln_IDs_201_231event] a
INNER JOIN
(SELECT appln_id,
count(case when withdr='1' then 1 end) as 'withdr_total',
count(case when oppos='1' then 1 end) as 'oppos_total'

UPDATE INDICATOR_TABLE_FINAL_MEASURES
SET      withdr =        b.withdr_total,
         oppos = b.oppos_total
         M [INDICATOR_TABLE_FINAL_MEASURES] i
INNER JOIN [INDICATOR_TABLE_Unique_Appln_IDs_201_231event] b
ON       i.appln_id = b.appln_id
```

Finally, in addition to the above commands which add information on patents' oppositions and withdrawals, the following SQL command adds information on the duration of patent renewals which are also utilized in subsequent steps in order to generate patent renewal indicators:

```
ALTER    TABLE INDICATOR_TABLE_FINAL_MEASURES
ADD      renewal_years varchar(50)

UPDATE   INDICATOR_TABLE_FINAL_MEASURES
SET      renewal_years           =       b.renewal_years
FROM     [INDICATOR_TABLE_FINAL_MEASURES] i
INNER JOIN
         (SELECT appln_id, AVG(CAST(fee_renewal_year as INT))
         as 'renewal_years'
         FROM    INDICATOR_TABLE_Unique_Appln_IDs_201_231fee_lapse
         _reinstate_extended_by_Han_ID
         GROUP BY appln_id) b
         ON      i.appln_id = b.appln_id
```

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The Impact of Available Financial Lending Resources on Firms' Patented Inventions*

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Abstract

This paper analyzes the impact of decreases in available lending resources on budgetary and qualitative dimensions of firms' patenting activities. For this purpose, the European Capital Exercise provides the basis for a quasi-natural experimental setup which is utilized in the empirical part of this paper. This exercise was conducted by the European Banking Authority in 2011 and required a subset of European banks to reach and maintain a 9 percent core tier 1 capital ratio, which was mainly achieved by a substantial reduction in their outstanding customer loans. The paper deploys information from the Patstat database which contains multi-fold data on the firms' inventive activities derived from bibliographic, procedural and legal patent data information. Furthermore, the Dealscan database provides additional information on firm-bank loan contracts, which are merged with firm financial data from the Amadeus database. Building on this unique, self-generated dataset, the results of this analysis support the 'less finance - less innovation' view. Higher bank capital requirements resulting in lower financial resources available for firm lending activities lead to less firm-level inventive activity in terms of budgetary patent measures. Qualitative dimensions of patented firm inventions, on the other hand, are affected positively and therefore support 'less finance - better innovation' considerations.

Keywords: patented inventions, financial resources, patents, corporate finance
JEL Classification: D22, G30, G31, G38, N24, O31, O34

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1 Introduction

It is widely accepted in the literature that innovation constitutes a driving factor for firm-level-productivity and economic growth (King and Levine 1993, Comin and Nanda 2014). It is, therefore, of great public interest to offer an economic environment which ensures that firms can engage in the development of new products or processes in a constructive manner. Firms' patents contain valuable information regarding measurable outcomes of their underlying inventions.[1] These inventions constitute the culmination of research activity and ideas, sketches or models of a new product of process which may often be patented (Swann 2009). Innovations refer to those (patented) inventions which are indeed commercially exploited (Bertoni and Tykvová 2015).

It is of particular interest to identify and analyze factors which affect firms' patenting outcomes. The availability of financial resources constitutes one important aspect for firms' innovative activities.[2] Findings in literature show that decreased available financial resources negatively affect innovative activities in quantitative terms, such as spending on R&D or the number of patents filed. However, simple input measures like expenditures on innovative activities have been questioned as adequate measures for firms' innovative performance, inter alia because they only give a very broad indication of their innovating activities, which have to be reported only if they are considered to be material. Also common output measures like the number of filed patents were argued to reflect only imperfectly the underlying value generated by firms' innovative activities (Lerner and Seru 2017). While the filing number of patents have reached unprecedented heights throughout the 2000s , key macroeconomic indicators such as labor productivity growth have been stagnating or even declining over the last decades (OECD 2017). The so-called 'more money, more innovation' story (Hottenrott and Peters 2012) has been questioned by pointing to possible beneficial impacts of financing constraints on the selection of more efficient innovative projects (Musso and Schiavo 2008, Almeida et al. 2013) – that is 'less money, better innovation' (Hall et al. 2015). Related theoretical considerations from the agency theory as well as neoclassical considerations suggest that decreases in the availability of firms' financial resources may be beneficial for *qualitative* dimensions of patented inventions.

Patent data contain valuable information regarding the measurable outcomes of firms' inventing activities of new products or processes. For instance, i) only those patent applications with a sufficient degree of novelty will be granted, ii) patents will only be filed in multiple countries if the underlying invention is perceived to be relevant in the respective areas with different jurisdictions, iii) published patents of higher technological or scientific relevance will be cited more often. From these information, data on multiple dimensions of patented inventions can be obtained. While these data do not directly capture their innovative character with respect to how path-breaking the inventions are in terms of their novelty,

[1] For instance, i) only those patent applications with a sufficient degree of novelty will be granted, ii) patents will only be filed in multiple countries if the underlying invention is perceived to be relevant in the respective areas with different jurisdictions, iii) published patents of higher technological or scientific relevance will be cited more often, and iv) only the valuable patents will be renewed annually by the patent holder.

[2] The term *innovative activity* may relate to numerous dimensions in order to capture firms' activities which are - more or less - directly linked to innovation. Therefore, it shall not be mixed with the above distinction between invention and innovation.

related measures on the innovative character of firms' patenting activities can be derived. For instance, the external perception and valuation of a patent can be analyzed with the help of information extracted from their citations. Furthermore, their technological relevance can be investigated in terms of their patent scope. Finally, their local applicability as well as their global value can be analyzed from the perspective of the patents' geographical scope.

Empirical literature so far has not analyzed how the availability of financial resources affects patenting activities, which are related to both, i) firms' spendings, i.e. the *budgetary dimensions* which are related to firms' patent filing costs, or the payments of associated fees based on the claims included in the patent documents , as well as ii) *qualitative dimensions* of the patented inventions - such as the received citations of the respective inventions, their geographical scope, withdrawals of applications by the patentees as well as the durations of the granting process. Analyzing these two dimensions within the same empirical setup is a promising field of research. In analogy to the 'more finance - more innovation' consideration, it could be expected that decreases in the availability of financial resources negatively affect the *budgetary dimensions* of patented inventions. Regarding the *qualitative* dimension, however, the 'less money, better innovation' consideration suggests that at a given level of financing, decreases in the availability of firms' financial resources might be potentially beneficial for qualitative dimensions of patented inventions. The following paper aims at investigating the impact of firm-level restrictions in the availability of financial resources on both, budgetary and qualitative dimensions. Therefore, a novel, self-generated panel dataset is constructed, which contains micro-level data from numerous sources and links information on individual firms' patenting activities obtained by the European Patent Office with firms' financial statements from Amadeus. These data are complemented with historical information on firm-bank loan contracts and credit lines from Dealscan.

The paper is amongst the first to conduct an in depth analysis of multiple dimensions of patented inventions in an European setup from a finance perspective. It analyzes how regulatory involvements in terms of increased banks' capital requirements, which have a negative impact on the availability of financing, affect firm-level inventive outcomes. For this purpose, the European capital exercise, which was introduced by the European Banking Authority (EBA) in 2011, is utilized as an instrument in a quasi-natural experimental setup. This capital exercise required a subset of European banks - which will be referred to as *EBA banks* - to increase their capital ratios and thereby reduce the availability of financial resources to the financing needs of firms.

Recent research results show that EBA banks increased their capital positions by more than 200 billion euro between December 2011 and June 2012 and raised their regulatory capital ratios by 1.9 percentage points compared to banks which were not subject to the higher capital requirements. This was achieved by reducing the levels of risk-weighted assets mainly by a strong reduction in outstanding syndicated customer loans (Gropp et al. 2018). Furthermore, those banks which did not have to recapitalize in the course of the EBA capital exercise did not substitute for those which had to increase their capital ratios in terms of increasing their lending resources (Mésonnier and Monks 2015), suggesting that these banks did not compensate for the decreased capital supply of the EBA banks. Finally, firms with a high EBA borrowing share were shown to exhibit 4 percentage points less asset growth and 6 percentage points less investment growth than firms less reliant on funding from EBA banks (Gropp et al. 2018).

The results of the empirical analysis support the view that less financial resources available to firms have a negative marginal impact on *budgetary* dimensions of patented inventions - such as on the number of patents filed and the number of claims included in a patent and are, therefore, in line with 'more money, more innovation' considerations from previous literature, which investigate other budgetary dimensions of firms' innovating activities. On the other hand, they have a positive marginal impact on certain *qualitative* dimensions of patented inventions - such as the forward citations received, the geographical scope, the grant lag or the withdrawals. These results are in line with the 'less money, better innovation' considerations. The established twofold picture constitutes a promising field for future research.

The remainder of this paper is structured as follows: section 2 summarizes the related literature and section 3 covers the hypotheses. Section 4 discusses the data used in this analysis. Section 5 contains the identification and empirical strategy. Section 6 presents the empirical results. Section 7 concludes.

2 Related Literature

The association between patents and inventions is widely accepted in the literature (Bertoni and Tykvová 2015). According to Swann (2009), inventions are the culmination of research activity and are ideas, sketches or models of a new product or process, that may often be patented. Going beyond inventions, innovations refer to those (patented) inventions which are indeed commercially exploited (Bertoni and Tykvová 2015).[3] Therefore, firms' patented inventions may be considered as one source of firms' potential innovations. Derived patent data, which contain potential insights on the commercial use of the patented invention such as quality weighted patent counts, have been used as proxies for innovation in empirical research (Hall et al. 2005).[4]

An invention is patentable, only if it is new and previously undisclosed, distinguished by an inventive step not obvious to someone expert in that technology and capable of industrial application (EPO 2019b). By guaranteeing a temporary monopoly for the underlying invention, patents are a prominent instrument for firms to safeguard their intellectual property.[5] The positive impact of patents increases the profits of the successful innovator to the monopolistic level (Boldrin and Levine 2013). This increases firms' incentives to engage in patenting activities (Aghion and Jaravel 2015).

[3]Another definition of innovation refers to Schumpeter (1934). According to this definition, an innovation refers to the introduction of either a new good or a new method of production Aside from this, Schumpeter also considers i) the opening of a new market, ii) the conquest of a new source of supply of raw materials or half-manufactured goods, and iii) the carrying out of the new organization of any industry as innovations.

[4]Several paper, however, use simple patent counts as measures of innovation (Cao et al. (2015)). See Bertoni and Tykvová (2015) with further evidence.

[5]Apart from this legal instrument to protect of intellectual property, alternative mechanisms to protect intellectual property are secrecy, complexity and lead time (Cohen et al. 2000, Hall et al. 2014, Png 2017). Other forms of formal intellectual property are trademarks, copyrights and designs. It is important to note that formal and informal instruments of intellectual property are not exclusive and they may be used in combination, for example when a manufacturer combines patents or secrecy with trademarks, complexity and lead time. For more details see Anton and Yao (2004), Graham and Somaya (2004), or Jensen and Webster (2009). However, even though complementaries between formal and informal instruments of intellectual property might exist, the implications of the analysis in this thesis only refer to patented innovations and therefore exclude other aforementioned instruments of formal and informal intellectual property.

Innovations are vital for firms as their survival may critically depend on their ability to successfully generate new answers to changes in competitive business environments (Lerner and Seru 2017). Therefore, it is of great interest to investigate key drivers of successful firm-level inventions. A comprehensive body of literature has investigated numerous determinants affecting firms' innovative activities (Souitaris 2002, De Jong and Vermeulen 2006), which can be classified into two broad areas: One strand of studies sets a focus on the identification of *internal firm characteristics* and their impact on firms' innovative behavior - such as firm size and firms' intangible assets (Shi 2017, Bontis 1998, Stewart 1997). Another strand of the literature analyzes the effect of *external sources* for firms' innovation - such as the competetive environment or the availability of external financial resources. Determinants from both areas will be discussed in this section.

The *firm size* is the first factor to be considered. Theoretical arguments have been put forward in favor as well as against the impact of firm size on innovation. On the one hand, it has been argued that the degree of firm-level innovation is positively correlated with its size (Schumpeter 1942). For instance, Galbraith (1952) argues that big firms may find it easier to internally generate funds which are required in order to run large research and development programs. Futhermore, large and diversified firms which operate in a wide field of economic activity may also have an advantage in capturing the value of new knowledge by patenting the resulting practical applications (Nelson 1959). On the other hand, bureucracy and red tape could restrain entrepreneurship and creativity in large firms (Belenzon and Patacconi 2008). Other studies argue that major innovations are conducted from small firms because these firms make use of new innovation opportunities whereas large firms supress these opportunities (Pavitt and Wald 1971). Incumbents might delay the development of new technologies to avoid the reduction of streams of rents from existing technologies (Arrow 1962, Reinganum 1984). It is also argued that small firms are more innovative in highly concentrated industries (Kamien and Schwartz 1975). Empirical literature on the relation between firm size and innovation shows that large firms are better equipped with resources than small enterprises in order to engage in risky and innovative activities (Majumdar 1995, Tsai 2001, Audretsch and Elston 2002, Becheikh et al. 2006). Ceteris paribus, firms' propensity to invest in research and development was shown to be positively associated with their size (Fisher and Temin 1973, Dosi 1988, Acs and Audretsch 1988).[6]

Firms' *intangible assets* constitute the next internal firm characteristic to be discussed. These assets can be devided into human, organizational and social capital (Stewart 1997, Bontis 1998). While all these dimensions are sources of firm innovation capabilities, theoretical considerations point out to the particular relevance of *human capital*, which is an essential part of innovation (OECD 2011, Sivalogathasan and Wu 2015). It contains skills, competence and intellectual agility of the employees (Roos et al. 2001) which cannot be owned by the firm (Bontis 2001). A major part of R&D is spent on expensive human capital, i.e. high-skilled workers. Therefore, it is a key knowledge resource of a firm, having substantial influence on the creation of new technologies (Romijn and Albaladejo 2002, Simonen and McCann 2008, Batabyal and Nijkamp 2013). It was shown that the growth of a firm is positively related to the quality of human capital

[6] See (Cohen and Levin 1989) for detailed literature review on past empirical findings.

and the firm's investment in it (Gössling and Rutten 2007, Santos-Rodrigues et al. 2010). Furthermore, as most firm-level innovations are incremental, it was shown that human capital is essential for the generation, adaption and diffusion of technical and organizational change (Toner 2011, McGuirk et al. 2015).
Finally, *social capital* consists of trust and trust-based networks of relationships which facilitate cooperation and coordinated work (Thompson 2018, Ahn and Kim 2017). Underlying theory argues that established relationships among individuals or organizational units within a firm are a source of knowledge creation and innovation (Nahapiet and Ghoshal 1998, Dakhli and De Clercq 2004, Parker et al. 2016). In line with these considerations, empirical literature has found that social climate and relationships faciliate the development of employee capabilities in order to combine and exchange information and create new knowledge (Donate and Guadamillas 2015, Collins and Smith 2006, Bowen and Ostroff 2004, van Reijsen et al. 2014).

Besides these internal firm characteristics, *external sources* also have an impact on firms' innovative activities. In line with the industrial economics theory associated with the resource-based model of the firm, not all resources required for innovation have to be owned by, or must be internal to the organisation (Teece 1986). It is a central finding in the literature that in many cases firms' innovation heavily depends on external resources (Fagerberg et al. 2006). These include - inter alia - the competitive relation of a firm with other firms and institutions as well as the availability of external financial resources.[7]
Regarding *competition*, it was argued that - from a firm's perspective - a more competitive environment reduces the expected payoff from research and development, thereby reducing R&D expenditures and leading to a lower rate of innovation (Schumpeter 1934). On the other hand, it was claimed that competition forces firms to innovate in order to survive which results in an boost of innovative activities (Porter 1990). In a theoretical model, an inverted u-shape relation was established between innovation and competition, according to which competition has a positive impact on innovation when the competition level is low, while at high competition levels, investments in innovation decrease as competition increases (Aghion et al. 2005). These predictions were underpinned by different recent empirical analyses (Tingvall and Poldahl 2006, Shi 2017).
The other external resource, which is of particular interest for the paper at hand, relates to the availability of external financial resources. The availability of these resources has a substantial impact on firms' innovating activities (Brown et al. 2009). Firm-level investments in innovation contain numerous characteristics which make it particularly challenging to finance them compared to other investments. Innovative activities are risky, and sometimes radically uncertain (Hall et al. 2015). The distribution of returns on innovation projects are highly skewed and only few innovations have particularly high returns, whereas many innovative projects do not generate returns at all (Scherer and Harhoff 2000). These particularities result in substantial opaquness and information asymmetry between innovating firms and capital providers, which exacerbate problems of opportunistic behavior (Hall and Lerner 2010, Kerr and Nanda 2015, Lerner and Seru 2017). They have negative consequences for both, firms' equity financing - as investors discount uncertainty on financial and stock markets, as well as their debt financing - when collateralisation becomes

[7] A more detailed overview containing further external resources can be found in Shi (2017).

prohibitive or even impossible (Hall et al. 2015).

Due to the complexity and high degree of uncertainty of innovative activities, raising external funds is subject to difficulties for firms and a hierarchy of preferred funding sources can be derived. In line with the pecking order theory introduced by Myers and Majluf (1984), innovative firms are likely to be more reliant on internal sources of funds and favor debt over new equity among external sources to avoid relative high dilution costs (Aghion et al. 2004).[8] Whenever internal resources are not sufficient, the inherent riskiness and intransparency of innovative activities may result in a mismatch between the demand for funding of innovative activities and the willingness of market participants to supply appropriate amounts of funding (Bellucci et al. 2014). These factors may also induce banks, which constitute important providers of external funding, to shorten credit even for positive net present value projects if the information asymmetries are too high (Berger and Udell 2006, Stiglitz and Weiss 1981). This would result in financial constraints and market failure in innovation (Hall 1992). Therefore, financial constraints should have a negative impact on quantitative innovative outcomes, given that they are considered as a specific type of investment activity. In analogy to the 'more money, more innovation' consideration, firms may have to forgo some of their innovation projects once they have restricted access to external financing regarding investments in innovation projects (Hottenrott and Peters 2012). Profitable investment opportunities might not be realized. In order to smoothen expenditures for research and development over time (Hall et al. 1986) and to compensate for these negative financial shocks (Lööf and Nabavi 2015), firms build up cash reserves. Still, this does not exclude for the possibility of financial constraints to arise and affect firm-level innovative activities, if these reserves were not sufficiently high. Negative financial shocks were found to have negative impacts on long-term innovative investments (Aghion et al. 2009) and firm innovativeness in general (Brancati 2015).[9] It is argued in the literature that firms which engage in innovative activities rely more on equity than on debt in order to finance their innovative activities (Falato et al. 2013, Brown et al. 2009, 2012). One explanation provided for these firms to do so is that they do not have sufficient amounts of collateral. Recent findings in the literature, however, underpin the importance of debt for firms' financing of innovation (Kerr and Nanda 2015). It was shown that a substantial amount of patenting firms increasingly gained access to debt financing if patents were pledged as collateral. As such, in 2013 over 38% of innovating firms in the United States utilized patents as collateral for receiving bank debt and these firms performed 20% of R&D and patenting based on Compustat (Mann 2018). Therefore, formal intellectual property may acquire the structure of a tangible asset, which in turn facilitates the provision of bank financing (?Mann 2018). Furthermore, it was shown that firms with substantial patent activity and high-quality patents receive cheaper bank loans than their peers (Chava et al. 2017). In addition, it was shown that firms utilize their

[8] Regarding young and innovative firms, some authors claim to observe a reversed pecking-order in which internal finance and equity have advantages over debt. For further details, see Hellmann and Stiglitz (2000).

[9] Another strand of literature analyzes the effect of positive exogenous shifts in the supply of credit on innovative activities. It is found that financial slack promotes patenting activities of affected firms (?Amore et al. 2013, Cornaggia et al. 2015). Furthermore, Brown et al. (2009) find that exogenous increases in the supply of finance lead to more spendings on R&D. Furthermore, it was found that financial frictions lower firms' investments in innovative projects, thereby inhibiting future productivity growth (Levine and Warusawitharana 2017). Recently, the great financial crisis served as a prominent event to investigate the impact of an exogenous negative shock in credit supply and several studies confirmed theoretical predictions that decreased supply was strongly negatively correlated with real economic activities, such as investment (Ivashina and Scharfstein 2010, Campello et al. 2010, Duchin et al. 2010).

patents and prototypes in order to signal the feasibility of a project and their ability to appropriate the returns from their innovation (Audretsch et al. 2012). Therefore, innovation can have a positive impact on external financing, if the potential creditor perceives the signal of a project to be credible. Based on these considerations, the complementarity of a reliable patenting system and a competitive environment may thus enhance corporate innovation (Aghion et al. 2015).

The paper at hand analyzes how regulatory involvements in terms of increased capital requirements for banks introduced by the European Banking Authority (EBA) in 2011, affect firm-level innovating outcomes. This capital exercise is well suited for investigating the impact of financial resources on firms' inventing activities due to the following reasons: First, the EBA measures have been criticised for having contributed to a credit crunch in the euro area.[10] Recent empirical findings support this notion. It was shown that EBA banks - i.e. the subset of European banks which had to increase their capital ratios in the course of this capital exercise - raised their regulatory capital ratios mainly by a strong reduction in outstanding syndicated customer loans compared to banks which were not subject to the higher capital requirements (Gropp et al. 2018). Furthermore, those banks which were not part of the EBA capital exercise did not substitute for the EBA banks in terms of available lending resources which indicates that the capital exercise had tangible procyclical macroeconomic effects (Mésonnier and Monks 2015). Firms with a high borrowing share at EBA banks were shown to exhibit less asset growth and investment (Gropp et al. 2018). Further related literature also shows that banks' capital requirements have a strong impact on their lending capabilities (Gambacorta and Mistrulli 2004, Altunbas et al. 2014). These requirements are typically linked to the individual bank's amount of outstanding credits. If violations to them are costly, banks aim at minimizing their risk of future capital inadequacy (Van den Heuvel 2002). As a consequence, stronger capital rules may result in immediate adjustments in banks' lending amounts, because capital raises may become very expensive or even unfeasible - particularly in periods of financial distress. Accordingly, stronger capital requirements may limit banks' lending abilities and decrease their credit supply towards potential borrowers (Gambacorta et al. 2011). Shocks regarding banks' capital requirements may result in restrictions in the external supply of capital, thereby propagating from the financial to the non-financial sector and having effects on real economic outcomes.

3 Hypotheses

Following these theoretical considerations and empirical findings from previous literature on the negative impact of insufficient financial resources on costly innovative activities, in a next step the first hypothesis regarding the *budgetary* dimension of the patented inventions are derived. The associated measures analyzed in this context are related to the firms' budgets as they are insightful with respect to the associated costs of their inventive activities, such as the number of filed patent applications as well as information

[10]See the statement made by ECB President Mario Draghi on January 12, 2012 in response to questions by journalists : "I think there are usually, by and large, three reasons why banks may not lend. . . . The second reason is a lack of capital. . . . So your question is about the second, a lack of capital. Now, the EBA exercise was in a sense right in itself, but it was decided at a time when things were very different from what they are today. . . . So in itself under these circumstances the EBA exercise has turned out to be pro-cyclical." (ECB Press Conference, 12 January 2012)

regarding the payments fees related to the claims included in a patent document.[11] Based on the above-described considerations, the first hypothesis relates to the impact of the negative exogenous shock in the availability of financial resources - modeled utilizing the EBA capital exercise - on *budgetary* measures of patented inventions:

H1: A negative exogenous shock in the availability of financial resources affects *budgetary* dimensions of firms' patenting activities *negatively*.

Besides these negative effects of financial constraints on innovative inputs and outputs, recent findings analyzing U.S. firms indicate that financial obstacles may benefit *qualitative* outcomes of innovation. The underlying 'less money, better innovation' consideration constitutes a relevant field of research, as it has been shown for U.S. firms that innovative efficiency, which was improved in the presences of financial constraints and is measured in terms of patent citations scaled by R&D expenditures, is value-relevant and increases future profitability of firms (Almeida et al. 2013, Hirshleifer et al. 2013, Cohen et al. 2013). The effect was stronger for firms with high excess cash holdings and low investment opportunities. Building on these findings and for a European context, the paper at hand uses more-detailed patent measures capturing the qualitative outcomes of firms' innovative activities in order to get a more profound understanding on firms' innovative oucomes, which will support these recent findings. Furthermore, in another analysis it was shown that financial constraints are positively related with productivity growth in the short run. The interpretation of this result is that financially constrained firms have to cut their costs in order to generate the resources they cannot raise on financial markets which results in improved efficiency (Musso and Schiavo 2008). Finally, it was shown that conglomerates with active internal capital markets conduct less novel R&D and that conglomerates with more novel R&D tend to operate with decentralized R&D budgets (Seru 2014). Apart from this, empirical evidence on potential beneficial effects of financial constraints regarding innovative outcomes is rare.

In the following, theoretical considerations will be discussed which provide potential explanations for the above-described findings from previous literature as well as regarding a potential positive impact of financial constraints on qualitative dimensions of patented inventions.[12] In this context, it is important to note that there is no consensus with respect to the formal definition of the quality associated with patented inventions (Squicciarini et al. 2013).[13] Supported by corresponding legal definitions, high quality patents can be defined as those which describe an invention that is truly new, rather than an invention that is already in widespread use but not yet patented (Hall et al. 2004). Following this consideration, high quality patents can be distinguished from their peers by their relevance, for instance, in terms of follow-up citations, their technological scope and particularities regarding the formal application process such as the

[11] A deeper discussion on the patent measures used in this paper follows in the data section.

[12] For terminological clarification it shall be remembered that the association between patents and inventions is widely accepted in the literature (Bertoni and Tykvová 2015). According to Swann (2009), inventions are the culmination of research activity and are ideas, sketches or models of a new product or process, that may often be patented. Going beyond inventions, innovations refer to those (patented) inventions which are indeed commercially exploited (Bertoni and Tykvová 2015)

[13] From an economic point of view, granting a property right described by a patent posts a trade-off between the gains from providing incentives for innovation against the deadweight loss implied by the potential monopoly during the patent term (Guellec and van Pottelsberghe de la Potterie 2007).

proper inclusion of prior knowledge in the application process. Therefore, a wide array of indicators can be derived, which mirror different, albeit often interrelated aspects of quality, having technological (e.g. backward citations), economic (patent claims) or both connotations (e.g. forward citations) (Squicciarini et al. 2013). Stakeholders agree about the necessity to raise the overall quality level of patented inventions worldwide. Low innovative quality is perceived to be influential with respect to decreasing incentives to innovate and triggering market failures which may harm innovation, growth, employment and welfare (Guellec and van Pottelsberghe de la Potterie 2007, Hall et al. 2004).

Theoretical explanations for the findings concerning beneficial effects of financial constraints on innovative outcomes can be established from numerous angles. According to Jensen (1986), managers have incentives to cause their firms to grow beyond optimal size, because growth increases managers' power when the resources under their control increase, resulting in higher compensation as well as reputation (Murphy 1985), which is also referred to as empire building. This may induce firms with excess cash flow, i.e. cash flow in excess of what is required to fund all projects with positive net present values, to invest in unproductive projects. A low availability of financial resources might force firms to make optimal investment decisions and avoid such agency problems (Almeida et al. 2013). Consequently, financial constraints might contain a disciplinary benefit, which is of particular relevance because agency problems are particularly severe in innovative investments (Kumar and Langberg 2009, Hall and Lerner 2010), as for instance Aboody and Lev (2000) find that investments in research and development are positively associated with information asymmetry and lead to substantial insider gains.

A second consideration is based on the approach to measure the marginal effect of an additional unit of financial resources on innovative outcomes. In line with previous empirical findings on quantitative innovative activities, a negative shock in the availability of financial resources may force firms to forgo some of their unexploited innovative projects (Hottenrott and Peters 2012). From the qualitative perspective, a rational firm would chose to skip those projects that appear least promising, for instance in terms of future returns. This could result in fewer projects being realized, however, with a higher expected innovative quality.

Finally, a third approach refers to bounded creativity considerations (Hoegl et al. 2008). The main idea is that constrained teams are forced to generate more creative ideas to overcompensate the lack of financial inputs. This strand of research builds on findings from cognitive psychology (Ward 1994), according to which thinking within a frame of reference, in this case limited resources, enhances the construction of novel ideas. Additionally, input resource constraints were found to induce teams to deploy the existing set of resources more economically, thereby increasing efficiency (Goldenberg et al. 2001, Moreau and Dahl 2005, Gibbert and Scranton 2009). These considerations also apply in the context of financial resource constraints. Literature in psychology has shown that financially unconstrained agents simply acquire the inputs needed for a well-known, previously experienced solution of a given issue (Scopelliti et al. 2014). Yet, Moreau and Dahl (2005) find that in the case of financial constraints, individuals come up with a solution that results in an equivalent outcome, despite the lower initial endowment. Hence, considering the previous insights, financial constraints may have beneficial effects on the outcomes of innovative activities.

However, sophisticated empirical analyses in an economic setup are rare so far.

Following these 'less money, better innovation' arguments, in a next step the second hypothesis on *qualitative* dimensions of patented inventions can be derived. The second hypothesis relates to the impact of a negative exogenous shock on the availability of financial resources - which is modeled utilizing the EBA capital exercise - on *qualitative* measures of patented inventions:

> ***H2***: A negative exogenous shock in the availability of financial resources affects *qualitative* dimensions of firms' patenting activities *positively.*

In the empirical part of this paper, multiple patent measures which serve as indicators for the qualitative outcome of the inventing activities will be considered. These include information the patents' received forward citations, the geographical scope in terms of patents' family sizes, the length of the granting procedure as well as information on withdrawals of applications.[14] In the following empirical analysis, the two hypotheses derived in this section will be discussed. Beforehand, the underlying data, including a detailed overview on the measures relating to the different dimensions of patented inventions will be discussed.

4 Data

The paper at hand is based on data from numerous sources. Information on individual firms' patenting activities are derived from the Patstat database which is provided by the European Patent Office. Information on firms' financial statements are taken from the Amadeus database which is provided by Bureau van Dijk. Historical information on firm-bank loan contracts are taken from the Dealscan database, which was obtained from Wharton Research Data Services. The following subsections provide a detailed overview on the data obtained as well as on the merging procedure of the utilized databases.

4.1 Patent Data

In this subsection, measures on *qualitative* and *budgetary* dimensions of patented inventions are discussed. These measures are derived from the Patstat database, which is provided by the European Patent Office (EPO). The EPO is an active member of the Patent Statistics Task Force which is led by the OECD.[15] On behalf of OECD, the EPO has prepared a database designed to assist in statistical research based on patent information. Patstat consists of three individual products. Patstat Biblio constitutes the core of the Patstat database. It has a worldwide coverage and contains raw bibliographic information about applications and publications for over 100 million patent records and 90 patent issuing authorities. Bibliographic data contain, amongst others, information on the names of applicants, technology classes, procedural information, the legal status of patents, i.e. whether a patent was granted or not as well as information on

[14] A deeper discussion on the patent measures used in this paper follows in the data section. Besides this, in depth analyses on multiple patent measures can be found in Krzyzanowski (2019)

[15] Other members are the World Intellectual Property Organization (WIPO), the Japanese Patent Office (JPO), the US Patent and Trademark Office (USPTO), Korean Intellectual Property Office (KIPO), the US National Science Foundation (NSF) and the European Commission (EC), which is represented by Eurostat and by DG Research (EPO 2017a).

citations of patents. The remaining two datasets are Patstat Legal Status (contains in depth information about the legal status of patents) and Patstat Register (contains more detailed information on published applications and patents filed with the EPO) (EPO 2017a,b). Therefore, the Patstat database contains various information, which allow for a detailed analysis on multiple dimensions of firms' patenting activities. According to the European Patent Office, an invention is only patentable if it is new and previously undisclosed, distinguished by an inventive step not obvious to someone expert in that technology and capable of industrial application (EPO 2017a). Therefore, only technological and commercially applicable inventions can be patented.[16] Along this line, for instance not all patent applications will be granted, because certain applications do not fulfill the above described criteria. Beyond this dimension, several patent offices worldwide collect information which go beyond the application process itself. These information can be utilized in order to derive patent measures such as forward citations, information on patent families, legal events regarding oppositions and other relevant procedural events. Utilizing the information contained in Patstat, patent measures for different phases of a patent can be generated, starting from the application process and going beyond the granting phase. These multi-layered information and derived measure can refer to both, the *qualitative* and *budgetary* dimensions of patented inventions.[17]

The following section gives an overview of relevant patent measures capturing budgetary and qualitative dimensions. Most of these measures are not provided as readily available data in Patstat. Rather, based on the broad range of contained data, the patent measures have to be generated separately. Both, *budgetary* and *qualitative* patent measures, are defined on individual patent application basis. While many of the measures are time invariant by construction, corresponding firm-level patent measures will vary over time. This is due to the fact that firms file numerous patents over time with diverse individual patent measure outcomes. As a consequence, time-variant patent measures are generated which can be utilized in a panel-setup. In line with previous literature, the measures are generated as normalized variables by means of dividing the initial results by the maximum score obtained in the same year and technology field cohort over a 98% winsorized distribution in order to deal with technological fluctuations, spurious outliers as well as to adjust for potential institutional changes, for instance in patent office policies (Lerner and Seru 2017, Squicciarini et al. 2013). Details on patent measure specific evolvements over time, industry and firm countries as well as discussions on associated structural issues in context of patents filed by European firms can be found in Krzyzanowski (2019). In order to reduce the potential for distortion which may be caused by spurious outliers, indices are constructed over a 98% winsorized distribution, i.e. indicators below the 1st percentile are transformed into values corresponding to the 1st percentile and those indicators above the 99th percentile are set to the 99th percentile.

[16] Not every innovation is protected by a patent, either because some innovations cannot be legally protected through patents (e.g. if an the criterion of industrial application is not fulfilled or the innovation is not sufficiently new from a legal point of view), or the innovator deliberately chooses not to protect his innovation and prefers secrecy or open source access over patent protection (Png 2017).

[17] In their recent paper, Lerner and Seru (2017) mention some issues with patent data which are faced by researchers (in corporate finance and related disciplines). Furthermore, the patent-based indicators should be understood as proxies, because no information about the real use of the patented technologies are included in those indicators.

4.1.1 Qualitative Patent Measures

The quality of inventory outcomes can be investigated from numerous perspectives. High quality patents can be defined as those which describe an invention that is truly new and, therefore, be distinguished from peers by their relevance, for instance, in terms of follow-up citations as well as regarding their geographical scope of sought patent protection. Furthermore, quality may also refer to derived events during the patent grant process such as the associated grant lag and premature withdrawals. Consequently, a wide array of indicators can be derived, which mirror different, albeit often interrelated aspects of quality, having technological, economic or both connotations. In this subsection, those indicators which are utilized in this paper in order to empirically analyze the *less money, better innovation* considerations, are discussed and the underlying rationale for each measure is presented in context of related literature.[18]

Each individual patent application needs to contain references to those patents that contain the relevant and related background for the invention underlying the application. The first qualitative patent measure which is used in this paper relates to the *forward citations*, more precisely the number of citations a particular patent receives from subsequent patents after it has been published.[19] Under Rule 27(1)(b) of the European Patent Convention there is no obligation of patentees to provide a list of references describing the state of the art which are considered relevant to the patentability of the invention, i.e. there is no so-called duty of candour (Criscuolo and Verspagen 2008). Nevertheless, it is argued that inventors will include all prior art in their patent application. Inter alia, applicants might provide a very detailed documentation in order to avoid future objections from third parties and, following this, strengthen the bargaining power in courts (Akers 2000, Criscuolo and Verspagen 2008). Furthermore, the examination authority may add additional relevant patents as well as remove irrelevant patents if they were deemed not to be relevant for the respective patent (Alcacer and Gittelman 2006).[20] The number of forward citations mirrors the technological importance of a patent for subsequent technologies and was shown to indicate the economic value of patented inventions (Hall et al. 2005, Harhoff et al. 2003). Based on the considerations of Trajtenberg (1990), forward citations constitute a measure widely used by the literature which can be counted over different periods.[21] Following the rationale that inventors mention prior art in their applications, higher references to particular inventions imply to have a higher relevance for subsequent inventors (Dechezleprêtre et al. 2017). Therefore, the number of received forward citations mirrors the technological importance of a patent for subsequent technologies which was also shown to indicate the economic value of patented inventions. The higher the estimates on the inventions' economic value were, the more the patents were subsequently cited (Harhoff et al. 2003). Numerous empirical studies have verified these findings utilizing different data and methodologies (see for instance Gambardella et al.

[18]While empirical literature predominantly focuses on citation measures, this section also includes other, less frequently used qualitative patent measures.

[19]It needs to be noted that patent literature cannot be cited before it is published, except for an invention is applied for by the same applicant (OECD 2009).

[20]The references included in patent documents mainly concern the relation towards other patents. Besides this, and to a lesser extent, non-patent literature is also contained as references in patent documents, in particular in terms of related scientific publications (van Raan 2017)

[21]As publication typically occurs 18 months after the filing date of the patent, patents published within the last 5 years can be considered as reliable with respect to the forward citations variable.

(2008), Kogan et al. (2017)). Furthermore, it has been shown that forward-citation-weighted patents are strongly correlated with measures of firm value derived from financial market data (Hall et al. 2005, Moser et al. 2015) and that patents, which were renewed to full-term and thereby provided the maximum duration of patent protection, were significantly more cited than patents which expired before their full term was reached (Harhoff et al. 1999). Based on these considerations, forward citations have been utilized as proxies for patent value in analyses of R&D, innovation, and knowledge flows.

A further qualitative patent measure relates to the so-called *family size* of a patent, which refers to the geographical scope of patent protection and the number of patent office jurisdictions in which a particular patent seeks for protection. According to the Paris Convention for the Protection of Industrial Property from 1883, applicants have up to 12 months from the first filing of a patent application in order to seek for patent protection in other jurisdictions and the right to claim the priority date of the first application (WIPO 2017, Squicciarini et al. 2013). For further applications at other patent offices, the priority date of the first application can be claimed. The set of these patents, which are related by common priority filings, is referred to as a patent family. The family size of patents is measured by the number of patent offices at which a given invention is filed (Squicciarini et al. 2013).[22] According to findings from previous literature, patent value is associated with the geographical scope of patent protection, since the decision to protect an invention at different patent offices reflects the willingness of the owner to translate the patent in different languages, deal with different national laws and invest more time as well as other resources in order seek for international patent protection (OECD 2009, Putnam 1997). Furthermore Harhoff et al. (2003) found in their survey analysis of German held patents that family size is correlated with estimates of the value of patent rights. Furthermore, Lanjouw and Schankerman (2004) found in an US setup that there is a a strong positive relationship between a patent quality index and their family size. Finally, from a European perspective, a positive relation between patent family size and the likelihood of the European patent to be granted could be established (Guellec and van Pottelsberghe de la Potterie 2000). Based on these considerations, information on patent families are used by researchers as proxies for patent value.[23]

The third measure which relates to the qualitative dimension of patented inventions refers to the time span until a patent is granted by the competent authorities, i.e. the *grant lag* of a patented invention. It is defined as the duration between the filing date of the application and the date of grant. The invention contained in a patent application is only patentable if it is new and previously undisclosed, distinguished by an inventive step not obvious to someone expert in that technology and capable of industrial application (EPO 2017a). Therefore, only technological and commercially applicable inventions can be patented. According to the literature, the value of a patent and the length of the grant lag period are inversely related to each other and that more controversial claims lead to slower grants (Harhoff and Wagner 2009). Furthermore, applicants try to speed up the grant procedure for their most valuable patents e.g. by careful

[22] More details on the concept of patent family size measures can be found in Krzyzanowski (2019).

[23] As family size is comparable internationally and contains information regarding the value of a patented invention, this measure is well suited for studies which rely on patent applications that are filed in different jurisdictions (de Rassenfosse et al. 2014). In this vein, other related literature has shown that patents filed at different patent offices are a good indicator of countries' research productivity (de Rassenfosse and van Pottelsberghe de la Potterie 2009).

documentation of these applications and closely sticking to the rules and procedures of each patent office (Squicciarini et al. 2013) which is also supported by empirical findings (Régibeau and Rockett 2010).[24]

Furthermore, the value of a firm is significantly affected by the technological breadth of patents owned by a firm, i.e. the *patent scope* (Lerner 1994). This variable captures the technological breadth of a patent application by counting the distinct International Patent Classes (IPCs) included in a patent application. Given that inventions can be considered to be combinations of existing ideas, the wider the set of ideas, the more valuable the patent (Guellec and van Pottelsberghe de la Potterie 2007, Dechezleprêtre et al. 2017). The IPC is based on Standard ST. 8 of the World Intellectual Property Organization (WIPO) and consists of the first 4 to 8 characters of an IPC class symbol.[25] The primary objective of the IPC is - by means of obtaining an internationally uniform classification of patent documents - to establish an effective search tool for the retrieval of patent documents by intellectual property offices and other users. Furthermore, the IPC classification creates a basis in order to investigate the state of the art in a given field of technology as well as for the preparation of industrial property statistics which permit the assessment of technological development in various areas (WIPO 2018).[26]

As a final measure, the *withdrawals* of patent applications are considered. According to the official Guide for applicants regarding how to get a European patent (hereinafter: EPO-Guide), the EPO establishes the state of the art of the patent application within the EPO procedure which contains information on the relevant prior art to the applicant and the examining devision (see recital 144 of the EPO 2019a). After the publication of this search report, the applicant has six months in order to file a request for examination. If this request is not filed, the application is deemed to be withdrawn (see recitals 146, 155 of the EPO 2019a). The search report may contain evidence that the claimed invention is not novel or does not involve an inventive step. Indeed, it was shown that applicants tend to withdraw their applications when the result of the search report was negative, thereby reflecting an expected refusal of the application (Schneider 2007). It was shown by Harhoff and Wagner (2009) that 26.5% of the EPO patent applications are withdrawn by the applicants after receiving a sufficiently negative search report. If the applicant requests the subsequent examination, the application is examined by the patent office according to its novelty, the associated inventive step and the industrial applicability. During this examination process it is still possible for the applicant to withdraw the application (see recitals 156, 157 of the EPO 2019a). Besides this, it is also argued in the literature that patent withdrawals can be interpreted as a signal which indicates that the patentee considers the continuation of the patent application process not promising in relation to the expected marketability and the expected profit of the potentially granted patent due to the relative low quality of the underlying invention (Long and Wang 2019).

[24] More details regarding particularities of the grant lag measure can be found in (Krzyzanowski 2019). A normalization of this quality measure is particularly important in order to control for possible examination backlogs and the increasing workload that may characterize certain years.

[25] see Chapter 6.77 and 6.79 of the EPO Biblio and Legal Data Catalog (EPO 2017a).

[26] Further details regarding different specifications of the patent scope measure can be found in Krzyzanowski (2019).

4.1.2 Budgetary Patent Measures

In order to investigate also the first hypothesis, patent measures relating to firms' *budgetary* dimension of patented inventions are generated. One standard measure refers to the total *number of patents* which were applied for by a firm at different patent offices, as for instance according to Article 2 (1) of Rules relating to Fees of the European Patent Convention, each European patent application is associated with corresponding filing fees. Besides this, also other national patent offices require the payment of application fees.[27] Another measure which is considered to capture budgetary dimensions of firms' inventive activities refers to the *claims* of a patent which gives a clear and concise definition regarding the scope of what the patent legally protects (OECD 2009, Squicciarini et al. 2013). The list of claims depicts the content of the claimed field of exclusivity. Recent descriptive analyses indicate that changes in associated claim fee structures included in patent applications have an impact on the number of patent claims included in the respective patent applications (Krzyzanowski 2019). Therefore, while patent claims were also shown by previous literature to be insightful with respect to the underlying value of a patented invention, they are considered as a budgetary patent measure in context of this paper due to their direct link to the costs of the underlying patent.[28]

4.2 Firm Financial and Bank Loan Data

Data on firm financials are obtained from the commercial Amadeus database which is provided by Bureau van Dijk. This database contains financial information on 21 million public and private companies across Europe and includes standardized consolidated and unconsolidated annual accounts data on company financials from balance sheets and profit-loss statements. Data is collected and harmonized by Bureau van Dijk such that comparisons of firms across countries are possible. Information from firm financials will be utilized as control variables in the empirical part of this paper.

Data on individual firm-level loans are obtained from the Thomson Reuters LPC Dealscan Database. This database contains comprehensive historical information on loan pricing and contract details, credit lines as well as on the terms and conditions and maturities of loans. Dealscan constitutes the world pre-eminent source for extensive and reliable information on the global commercial loan market with a focus on syndicated loans (WRDS 2019). More than 70 percent of the sample data is on non-US-firms.

4.3 Data Merges

While the above described databases contain detailed information regarding their specific scope, it is necessary to combine them in order to tackle the research question of this paper. Without any financial data, information on patents (and vice versa) would not suffice for analyzing the impact of a negative shock in the availability of financial resources on budgetary and qualitative outcomes of firms' inventing

[27] For more details, see for instance (DPMA 2019).

[28] Note that for example considerations regarding patent family size from above might also be related to *budgetary* measures. However, it can be argued that the decision to file a patent application with more or less claims is rather related to the associated costs of additional claims while the decision to file for patent protection in more or less countries is rather related to the value of the underlying invention which justifies protection at an international level.

outcomes. Furthermore, firm-bank loan-relationships are essential for the identification strategy of this paper, which will be presented in the next section.

The Patstat and Amadeus databases do not share a common identifier. Therefore, a sophisticated matching algorithm is needed which allows to link data from both sources with sufficient confidence. It is important to note in this context, that the data provided by the Patstat database are close to raw state and, therefore, have not undergone any form of standardization. Thus, several issues might arise, such as incorrectly spelled names, unstandardized addresses, misspecification of countries to patent applicants, or, in general, missing data in Patstat (Peruzzi et al. 2014).

Overview - Data Merges and Sample Dataset

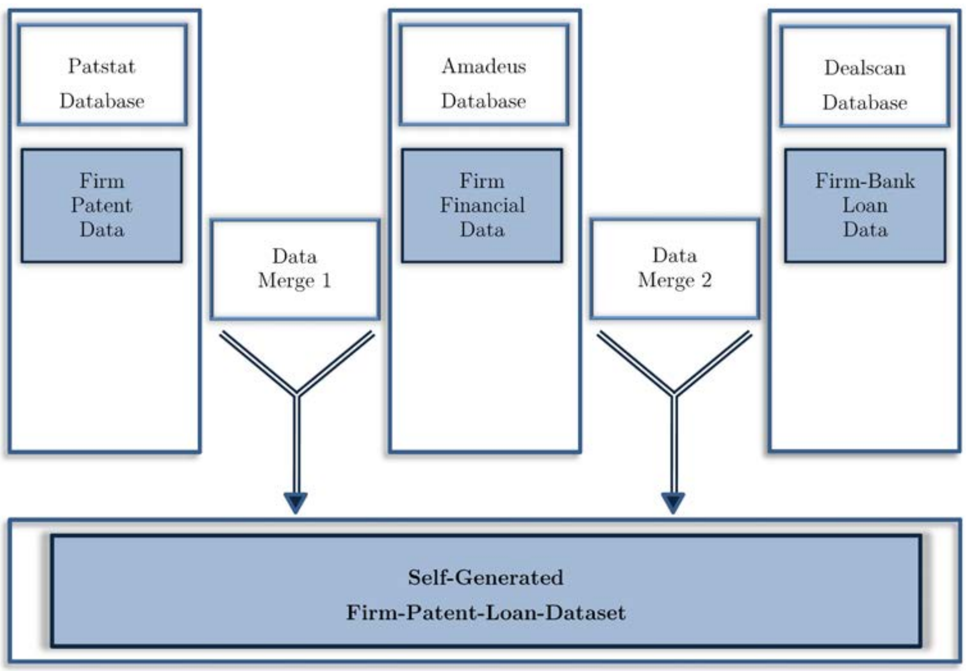

Figure 1

In order to link firms from Patstat to those from the Amadeus database, in a first step substantial data cleaning operations are needed. This allows to overcome the above described data ambiguities by transforming the available information contained in Patstat in a meaningful way. In a second step, based on the transformed data in Patstat, a sophisticated data matching algorithm is needed. For this purpose, the record linkage algorithm established by Peruzzi et al. (2014) is utilized in this paper. Further details regarding the matching algorithm utilized can be found in the Appendix of this paper. Following this, in a next step information from the Dealscan database are added to the Patstat-Amadeus database. For this purpose, string distance matching algorithms based on firm names, addresses and country information are applied. Based on an estimated matching probability cutoff of 90 percent, the final self-generated bank-firm-level innovation panel dataset is established (see Figure 1 above).

4.4 Supplementary Data

Additionally to these firm-specific data, sector- and country-specific control variables are included in the analysis. Data on country-specific macro controls are obtained from OECD's statistical database, OECD.Stats. Further controls are obtained from the European Central Bank (ECB) Statistical Data Warehouse and the World Bank DataBank-database. A list of all firm-level and macro-level control variables is provided in the Appendix. Data included in the analysis cover the time range from 2000 until 2014. This time frame includes the financial crisis preceding the capital exercise and excludes the most current years in order to deal with truncation issues regarding patent measures as well as the rationale that restrictions in the availability of financial resources will have a lagged effect on respective firms' innovative activities. Firms from the financial sector are excluded as well as those that have no total assets reported in a given year. To avoid survivorship-biases, firms can freely enter, respectively drop out the dataset. However, firms that do not appear at least for three consecutive years in the dataset are excluded. Also, all financial variables are normalized by total assets, if not indicated otherwise. The final sample comprises an unbalanced panel dataset for around 200 firms resulting in about 1800 observations.

Based on the above considerations regarding the construction of the final dataset, the following descriptives provide insights on selected characteristics of the firms which are contained in the empirical part of the paper. In order to provide relational descriptives regarding the properties of those firms engaged in patenting activities for which the information from Patstat can be merged to Amadeus and Dealscan, selected statistics are provided which allow for comparing properties of these sample firms to those of all firms contained in the Amadeus dataset utilized for the data merge above. Notably, during the above-described matching processes, only those matches were utilized in the empirical part of this paper which constituted - with sufficient confidence - true matches. This condensed the firms included in the empirical analysis. Therefore, the following part gives insights on how the matched firms included in the empirical analysis of this paper differ from the set of all firms included in the Amadeus dataset with respect to selected financial dimensions. From Table 1 below, it can be seen that the sample firms involved with inventive activities are on average ten times bigger in terms of their total assets compared to all firms included in the Amadeus dataset. Besides this, the sample firms are quite similar in terms of their leverage as well as their equity ratio and their EBITDA to assets ratio, while the cash ratio of the sample firms is significantly smaller compared to those of the Amadeus firms. Therefore, while the inventive firms from the sample appear to be bigger than the set of all firms included in Amadeus, they appear to be rather similar in terms of selected financial accounting ratios. The empirical analysis and derived results which will be conducted in the next subsection, should be interpreted in light of these descriptive findings.

Descriptive Statistics – Amadeus Firms vs. Sample Firms						
		Total Assets (mn)	Debt Ratio	Equity Ratio	EBITDA/Assets Ratio	Cash Ratio
	Mean	26	0.66	0.34	0.14	0.16
	p25	0.4	0.43	0.15	0.06	0.01
Amadeus Firms	Median	2.1	0.66	0.34	0.11	0.07
	p75	10	0.85	0.58	0.18	0.22
	Std. Dev.	102	0.38	0.42	0.11	0.20
	Mean	295	0.61	0.39	0.13	0.07
	p25	46	0.46	0.25	0.07	0.01
Sample Firms	Median	158	0.62	0.38	0.12	0.04
	p75	434	0.94	0.54	0.17	0.10
	Std. Dev	334	0.28	0.29	0.08	0.13
Diff.		269	-0.047	0.049	-0.006	-0.08
P-Value	*(diff = 0)*	*0*	*0*	*0*	*0*	*0*

Table 1

5 Empirical Strategy and Identification

In order to analyze the impact of a negative shock in the availability of financial resources on firm-level patenting activities, the capital exercise conducted by the European Banking Authority in 2011 will be utilized in a difference-in-difference estimation setup. Controlling for firm-, industry-, and macro-specific variables, the EBA capital exercise provides a quasi natural experiment in order to analyze how the associated shock affects innovation in terms of the different dimensions regarding patented inventions for those firms which are classified as being exposed to the consequences of the exercise. The treatment is defined as the exogenous introduction of the increased bank capital requirements affecting a subset of European banks, whereas the firms' exposure to the treatment is based on ex ante differences regarding their lending shares to the EBA banks, which will be defined below.

Heterogeneity in the sample will be utilized in two distinct ways. First, cross-country variation is introduced by the fact that the EBA banks were chosen based on their national relative market share in terms of their total assets in descending order of their individual share and covering at least 50% of the respective national banking sector as of 2010. As national banking sectors differ with respect to their sizes, the banks included in the EBA capital exercise will be somehow disentangled from bank size factors by including banks from different countries with different sizes in the capital exercise.

In addition to this, within-country variation arises from differing degrees of firms' exposure to to the treatment. It has been shown that EBA banks substantially reduced the amount of their outstanding syndicated loans following the EBA capital exercise. The exercise was criticized for having contributed to a credit crunch in the euro area (Degryse et al. 2019, Mésonnier and Monks 2015). Notably, it was reported after the first announcement of the capital exercise in October 11, 2011 in the *Financial Times* that the 9 percent requirement lied “well beyond the current expectations of banks and analysts ” (Gropp et al. 2018). As a result, firms with a high EBA borrowing share exhibit inter alia 4 percentage points less asset growth and 6 percentage points less investment growth[29] than firms less reliant on funding from EBA banks. One provided explanation for these findings is that once the EBA banks decrease their amounts of outstanding loans, high switching costs make it relatively more difficult for firms to obtain new financing if they were previously more engaged with these EBA banks. Furthermore, limited access to other sources of external funding could explain why EBA firms were not able to obtain other sources of external funding, inter alia because banks which were not constrained by the EBA capital exercise did not substitute for those which had to increase their capital ratios (Gropp et al. 2018, Mésonnier and Monks 2015). In line with these findings and following related literature, the sample of firms in this paper is divided into EBA firms with an above median dependence on credit supply from EBA banks - measured by their EBA borrowing share - and the non-EBA firms with a below median dependence on credit supply from EBA banks.[30] The borrowing share of an individual firm j is calculated as follows:[31]

$$\text{EBA Borrowing Share}_{\text{j}} = \frac{\sum_{\text{i[EBA Banks]}} \sum_{\text{q=2010 Q1}}^{\text{2010 Q4}} \text{Loans}_{\text{ijq}}}{\sum_{\text{i[All Banks]}} \sum_{\text{q=2010 Q1}}^{\text{2010 Q4}} \text{Loans}_{\text{ijq}}}$$

In the nominator, the amount of outstanding loans of firm j towards the banks directly affected by the EBA capital exercise is depicted over the year preceding the EBA capital exercise. By analogy, the denominator refers to the amount of outstanding loans of firm j towards all banks incorporated in European and non-European countries. In line with the considerations from above according to which firms with higher EBA borrowing shares were negatively affected in the development of their assets and investments, EBA firms are considered as being exposed to the above-described negative impact of the EBA capital exercise on bank lending, whereas the non-EBA firms are considered as being not exposed to the EBA capital exercise. This classification, therefore, assumes that the EBA capital exercise does not have a uniform effect across the entire sample of firms. Rather, there exists between-firm variation regarding the degree to which they are are considered to be affected by increasing the capital requirements during the EBA capital exercise.As has been previously discussed, firms engaged in innovative activities can be considered as informationally relatively opaque. Therefore, switching of firms to alternative sources of debt, i.e. different banks may be even more difficult and associated with higher switching costs compared to more transparent firms (Yin and Matthews 2018). In order to address reverse causality concerns, the firms are classified into the treatment and control group based on their individual lending shares to the EBA-banks preceding the announcement of the EBA capital exercise based on the above described median-split of the firms’ EBA borrowing share as of 2010. Based on this classification, the following descriptives provide insights on how

[29]Fixed assets were used as a measure of investment, following Campello and Larrain (2015).

[30]An analogous classification was conducted by Gropp et al. (2018).

[31]In another paper, it is analyzed how differences in lending relationships towards EBA banks in terms of firms’ lending durations as well as the number of their banks affects firms’ inventive activities in context of the EBA capital exercise. The scope of the paper at hand, however lies in the classification of firms into treatment and control groups based on their *ex ante* lending exposure to EBA vs. non-EBA banks.

the firms exposed to the treatment, i.e. with above median lending shares at banks included in the EBA capital exercise, relate to the other firms classified as being not exposed to the treatment, i.e. with below median lending shares. In a first step, Figures 2 to 7 below depict distributional functions on selected firm financial and firm industry dimensions for both, the exposed as well as non-exposed firms which are included in the subsequent empirical analyses.

Figure 2

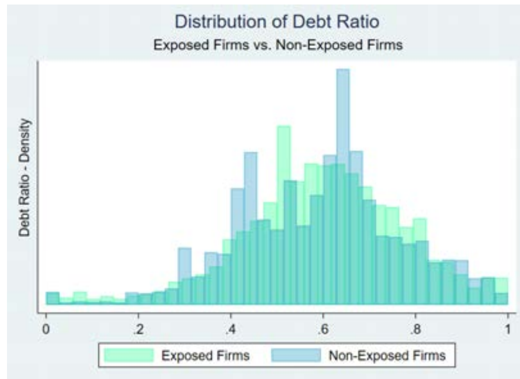

Figure 3

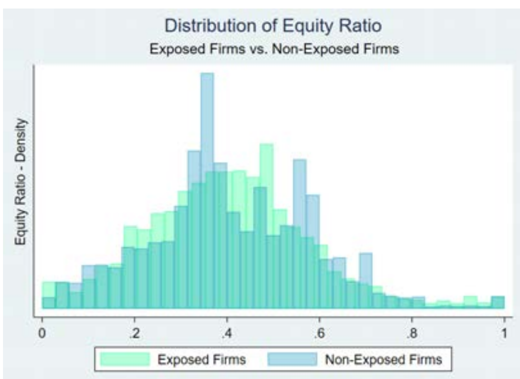

Figure 4

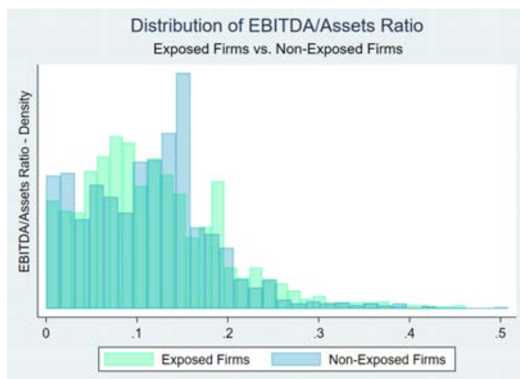

Figure 5

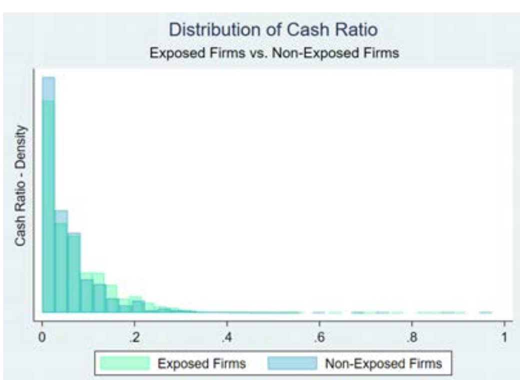

Figure 6

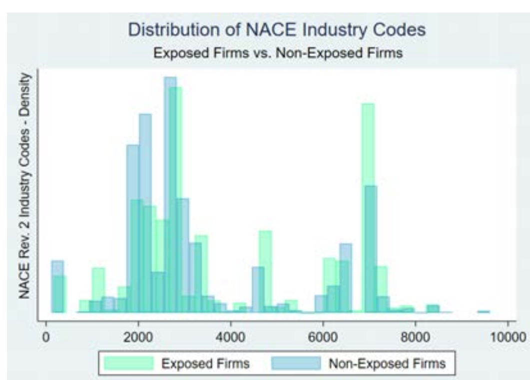

Figure 7

From the figures above, it can be seen that the distributions of the exposed firms included in the empirical analysis appear to be very similar compared to the distribution of non-exposed firms regarding the total assets, the debt and equity ratios as well as regarding the EBITDA-to-Assets ratio, the cash ratio and the NACE industries of the respective exposed and non-exposed firms. This notion is supported by further statistical analyses based on Goldman and Kaplan (2018) who introduce a statistical procedure for comparing distributions. The usage is similar to a two-sample t-test or a two-sample Kolmorogov-Smirnov test, however, in contrast to previous methods, it accesses the equality of distributional functions point by point (Kaplan 2018, Goldman and Kaplan 2018). Based on their methodology the null hypotheses of equality of the above-depicted distributions cannot be rejected at a 5 percent significance level for the distributional functions depicted above. Complementing these distributional comparisons, further descriptives on the exposed as well as non-exposed firms are provided in the appendix to this paper in subsection 8.2. Based on these comparative analyses, it can be ascertained that the ex-ante classification of firms exposed to the EBA capital exercise based on their lending share towards EBA banks does not result in major structural differences of those firms being classified into these different groups.[32] Out of this consideration it can be argued that the firms considered as being exposed and not exposed to the treatment to be relatively similar in terms of their geographical domestication and their industries. This finding is valuable for the below empirical difference-in-difference regression analysis. If there were substantial differences between the ex ante classified treatment and control group firms, it would be difficult to argue that differences in the impact of the EBA capital exercise could not potentially be confounded by structural differences in the treatment and control group of exposed firms.

The empirical challenge in context of changes in bank capital requirements is that they usually affect - once they change - all banks in a given economic area which would lead to no cross section variation. Furthermore, if discretionary bank-specific requirements were introduced, these might be correlated with observable bank characteristics and, therefore, not be exogenous to banks' balance sheets. However, due to the country-specific bank selection rule of the EBA capital exercise, which covered 50 percent of each national banking sector in descending order of banks' individual market shares, the necessity for increased capital requirements from 5% to 9% can be disentangled from bank size characteristics on a cross country basis, since national banking sectors differ with respect to their size and resulted in a considerable overlap between banks participating and not participating in the capital exercise (Gropp et al. 2018). Therefore, the variation in banks' capital requirements introduced by the EBA capital exercise can be considered to be exogenous. Furthermore, endogeneity should be less of a concern, because empirical estimates in this paper are calculated on firm-level basis, while implementation decisions of the EBA capital exercise are based on a country-bank-level.[33] Finally, the capital exercise can be considered as being exogenous regarding i) potential preemptive adjustments of banks' balance sheets which would bias downward the effects of the capital exercise on lending, as well as regarding ii) firms' bank choices and lending relations towards certain institutions in advance to the capital exercise due to the unexpected occurrence of the exercise (Mésonnier and Monks 2015, Gropp et al. 2018).

Following these considerations, in the next step additional descriptives are provided which aim at analyzing in what way the above defined exposure variable is meaningful for capturing the negative impact of the EBA capital exercise on the availability of firms' financial debt resources. As described above, previous

[32] Notably, exposed firms appear to be bigger in terms of their total assets while mean comparisons of the other financial measures do not result in statistical differences in means.

[33] Analogous argumentation to Schnabel and Seckinger (2015).

literature found that the banks which were directly affected by the EBA capital exercise strongly reduced their customer loans compared to those banks which were not subject to higher capital requirements, while firms with higher ex ante EBA borrowing shares were affected negatively in their asset and investment growth (Gropp et al. 2018). Building on these findings, the following regression analysis aims at providing insights as to how firms' debt accounts evolved over time based on the described exposure classification. If the capital exercise had no different impact on firms' debt for the exposed and non-exposed firms, it could be argued that the classification scheme would not capture decreases in available financial resources of the exposed firms relative to the non-exposed firms. If, however, decreases in firms' debt amounts could be observed for the ex ante exposed firms compared to the non-exposed firms, this descriptive finding would suggest that firms with ex ante higher EBA lending shares indeed faced decreased available financial resources following the EBA capital exercise, in particular because the exposed and non-exposed firms in the paper at hand were shown to be be depicted by very similar financial characteristics. Based on these considerations, the following fixed-effects, cross-section regression model is set up in order to provide insights as to how firms' debt accounts evolve over time based on the described exposure classification:

$$Firm\ debt_{itc} = \beta_0 + \beta_1 Exp_{ic} + \beta_2 X_{itc} + \phi_{nace} + \delta_c + u_{itc} \qquad , \forall\ t \in [2007, 2014]$$

In this equation, the $Firm\ debt_{itc}$ variable measures firm i's normalized short term bank debt in time t from firm-country c, X_{itc} resembles a vector of firm-level control variables, while ϕ_{nace} and δ_c depict industry fixed-effects and country fixed-effects, respectively. The exposure variable Exp_{ic} is an indicator variable which refers to the above described exposure classification based on their ex ante lending shares to EBA banks which is equal to 1 if a firm has an above median EBA borrowing share and zero otherwise. Based on this regression model, the adjacent figure contains the regression outputs on the exposure parameter β_1 for each year between 2007 and 2014, as well as corresponding 90% confidence intervals which are depicted by the bullets and whiskers, respectively. While the exposure coefficient estimates on β_1 are insignificant and close to zero from 2007 until 2010, it can be seen that there is a strong negative and statistically significant shift in the parameter in 2011 which also persists until 2012. This descriptive finding provides evidence that firms' short term bank debt did not evolve differently from 2007 until 2010 between the exposed and non-exposed firms, which indicates that their bank debt was depicted by similar developments also during the outbreak of the recent financial crisis. However,after the EBA capital exercise was conducted by the European Banking Authority, the exposure coefficient becomes significantly negative in 2011, which indicates that firms' short term debt amounts are indeed significantly lower for the exposed firms relative to the non-exposed firms. This descriptive evidence, therefore, suggests that the exposure classification scheme indeed captures decreases in available financial resources of those firms with hither ex ante borrowing shares at EBA banks.

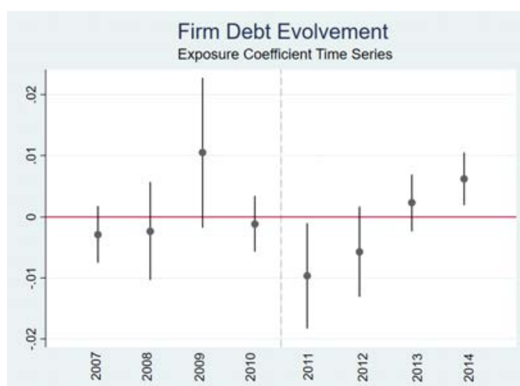

Figure 8

On this basis and in order to implement the identification strategy, a difference-in-difference approach will be utilized in which both, *budgetary* and *qualitative* dimensions of patented inventions, will be analyzed throughout the implementation phase of the EBA capital exercise. The panel structure of the data allow to control not only for unobserved heterogeneity across firms but also for entity-fixed but time varying effects. Since lending generally follows a cyclical pattern (e.g. Ivashina and Scharfstein (2010)), it is particularly important to control for year-fixed-effects, i.e. differences in lending conditions. Following Bertrand et al. (2004), standard errors are heteroskedasticity-consistent and clustered at the firm level. Furthermore, in order to address concerns regarding potential trend evolvements of the patent measures, lagged values on the growth rates of the dependent variables are included as additional micro controls. Based on these considerations, the difference in difference model is established:

$$\begin{aligned} Patent\ Measure_{itc} =& \beta_0 + \beta_1 Exp_{ic} + \beta_2 Post_{t-1} + \beta_3 (Exp_{ic} \cdot Post_{t-1}) \\ & + \beta_4 X_{ic,t-1} + \omega_{c,t-1} + \gamma_{t-1} + u_{ict} \end{aligned}$$

where $Patent\ Measure_{itc}$ refers to different variables referring *budgetary* or *qualitative* dimensions of patented inventions of firm i in period t from country c. The Exp_{ic} variable is a dummy variable capturing the above-described exposure of firm i from country c to the treatment, i.e. the EBA capital exercise. This variable is set to 1 if the firm is from the treatment group in either period in time based on the ex ante classification referring to the firm's EBA lending share. The $Post_{t-1}$ variable is a dummy variable set to 1 if the observation is from the post treatment period in either group. It is assumed, that the patent measures are affected with a one period lag by the treatment. This assumption is based on the consideration that it takes time for inventory outcomes to react to negative shocks in the availability of financial resources.[34] Further micro controls ($X_{ic,t-1}$), macro controls ($\omega_{c,t-1}$), and year controls (γ_{t-1}) are also included in the more sophisticated model specifications. Micro controls include the firms' logarithm of total assets, cash, equity, debt ratio, shareholder funds, net current assets, intangible as well as other fixed assets. Industry Fixed effects are based on the NACE Rev. 2 industry classification. Macro controls include measures on GDP per capita and GDP growth, balance of trade, labor productivity, R&D expenditures, a Financial Distress and a Financial Crisis Indicator for each of the countries. More details on the variables are depicted in the Appendix in subsection 8.1.

6 Empirical Results

This section contains the empirical results for the above-described difference-in-difference regression model. For each of the previously-discussed patent measures, the estimation outcomes depict the baseline specification with firm-level micro controls, as well as more sophisticated specifications with additional macro-level controls, industry fixed effects, country fixed effects and year fixed effects. The treatment is based on the execution of the European Capital Exercise vis-à-vis the EBA banks, whereas the firms' exposure to the treatment is based on the ex-ante median split of their lending shares towards these banks.

[34] Note that the robustness checks include different specifications of lag and lead structures in the analysis.

The first set of estimation tables provides the regression results on the *budgetary* patent measures which are related to i) the firms' patent filing costs by means of the number of patent applications filed, and ii) the payments of associated fees based on the claims included in the patent documents. According to the first hypothesis of this paper, the negative exogenous shock in the availability of financial resources following the EBA capital exercise is argued to have a *negative* impact on these inventive dimensions for the exposed firms based on their ex-ante lending shares towards EBA banks. Against this background, parameter β_3 is the coefficient of interest in the difference-in-difference regression model above: It precedes the interaction term between the treatment and exposure variable and, thereby, captures the treatment effect of the decrease in the availability of financial resources on the budgetary dimensions of the inventive outcomes with respect to the exposed firms. In the first column, the baseline difference-in-difference model includes additional micro control variables in order to estimate the regression parameters of the discussed patent measures. Moreover, the second column contains supplementary industry controls, while the specification in the last column integrates further macro controls as well as country and year fixed effects. Thereby, the third column contains the most sophisticated specification of the difference-in-difference model in order to estimate the regression parameters for the budgetary patent measures in the subsequent tables below. Starting with the patent measure capturing the number of firms' patent applications, the results of the above described three-fold model-specification are summarized below:

	Number of Patent Applications	Number of Patent Applications	Number of Patent Applications
Treatment	-0.011	-0.010	0.021
	(1.47)	(1.52)	(1.15)
Exposure	0.004	0.003	0.008
	(0.40)	(0.34)	(0.96)
DiD-Estimator	-0.001	-0.002	-0.014
	(0.17)	(0.30)	(2.15)**
Constant	-0.076	-0.109	0.016
	(3.25)***	(3.70)***	(0.34)
Micro Controls	YES	YES	YES
Industry Fixed Effects	NO	YES	YES
Macro Controls	NO	NO	YES
Country Fixed Effects	NO	NO	YES
Year Fixed Effects	NO	NO	YES
Adjusted R^2	.23	.26	.37
N	1942	1942	1857

Table 2 presents the firm-level regression results of the difference-in-difference model for the budgetary patent measure which records the number of the firms' patent applications in normalized terms in different model specifications. The sample consists of all firms in the intersection of Patstat, DealScan and Amadeus which are located in Austria, Belgium, Finland, France, Germany, the Netherlands, Sweden and the United Kingdom. The treatment is based on the execution of the European Capital Exercise vis-à-vis EBA banks, whereas the firms' exposure to the treatment is based on the ex-ante median split of their lending shares towards these banks. Micro controls include firms' logarithm of total assets, cash, equity, debt ratio, shareholder funds, net current assets, intangible as well as other fixed assets. Industry Fixed effects are based on the NACE Rev. 2 industry classification. Macro controls include measures on GDP per capita and GDP growth, balance of trade, labor productivity, R&D expenditures, a Financial Distress Indicator and a Financial Crisis Indicator for each of the countries. Details on the variables are depicted in subsection 8.1. Standard errors are adjusted for heteroscedasticity and clustered at firm level. Significance levels: * (p<0.10), ** (p<0.05), *** (p<0.01).

The estimation results in Table 2 on the parameter of interest β_3 are highlighted in the framed box and include the numerical outcomes on the DiD-Estimator, which captures the treatment effect in the different model specifications. While the estimated effect on β_3 is marginally negative and statistically insignificant in the baseline as well as the second specification, it increases in its negativity and becomes statistically significant at the five percent significance level in the most sophisticated specification. Consequently, this result provides support for the first hypothesis according to which the negative shock in the availability of financial resources has a negative impact on this budgetary dimension of the inventive outcome with respect to the exposed firms. As previously described, the patent measure on the number of the firms' patent applications is generated as a normalized index variable. Therefore, in terms of economic relevance, the estimation result on the treatment effect in the most sophisticated model specification indicates that the exposed firms file 1.4 percent less patent applications due to the EBA capital exercise relative to the non-exposed firms. Besides this, it is interesting to note that the estimates on the exposure parameter are insignificant in all three specifications. This indicates that there are no average permanent differences between the exposed and non-exposed firms regarding the number of patent applications filed by these firms. The estimates on the treatment, finally, capture the common time trend to the control and treatment groups which is insignificant in all model specifications. Overall, these regression results for the number of patent applications are supportive for the first hypothesis of this paper. The next table below comprises

	Patent Claims	Patent Claims	Patent Claims
Treatment	-0.030	-0.028	-0.045
	(1.56)	(1.78)*	(0.88)
Exposure	0.004	-0.003	0.009
	(0.18)	(0.22)	(0.60)
DiD-Estimator	0.009	0.002	-0.007
	(0.34)	(0.10)	(0.26)
Constant	0.156	1.007	0.462
	(2.66)***	(27.76)***	(1.48)
Micro Controls	YES	YES	YES
Industry Fixed Effects	NO	YES	YES
Macro Controls	NO	NO	YES
Country Fixed Effects	NO	NO	YES
Year Fixed Effects	NO	NO	YES
Adjusted R^2	.03	.23	.28
N	1925	1925	1841

Table 3 presents the firm-level regression results of the difference-in-difference model for the budgetary patent measure which records the number of the firms' patent claims in normalized terms in different model specifications. The sample consists of all firms in the intersection of Patstat, DealScan and Amadeus which are located in Austria, Belgium, Finland, France, Germany, the Netherlands, Sweden and the United Kingdom. The treatment is based on the execution of the European Capital Exercise vis-à-vis EBA banks, whereas the firms' exposure to the treatment is based on the ex-ante median split of their lending shares towards these banks. Micro controls include firms' logarithm of total assets, cash, equity, debt ratio, shareholder funds, net current assets, intangible as well as other fixed assets. Industry Fixed effects are based on the NACE Rev. 2 industry classification. Macro controls include measures on GDP per capita and GDP growth, balance of trade, labor productivity, R&D expenditures, a Financial Distress Indicator and a Financial Crisis Indicator for each of the countries. Details on the variables are depicted in subsection 8.1. Standard errors are adjusted for heteroscedasticity and clustered at firm level. Significance levels: * (p<0.10), ** (p<0.05), *** (p<0.01).

the regression results on the second budgetary patent measure which contains information on the costly patent claims included in a patent. While the treatment effect is negative in the most sophisticated model and therefore by itself in line with the considerations from the first hypothesis, it is statistically insignificant in all three specifications. Therefore, with respect to this budgetary measure, the difference-in-difference model does not provide evidence for differences between the exposed and non-exposed firms regarding the amount of claims contained in their patents. In summary, these regression results on the *budgetary* patent measures from Table 2 and Table 3 above suggest that the decrease in available financial resources due to the EBA capital exercise affect the exposed firms *negatively* in terms of the amount of their filed patent applications, while the claimed fields of exclusivity are not affected differently between these two groups.

In order to provide empirical results for the second hypothesis of this paper, in a next step analogous regressions on the *qualitative* patent measures are conducted which relate to i) the forward citations a patent receives from subsequent patents, ii) the geographical scope of patent protection, iii) the withdrawals of firms' patent applications and iv) the time span until a patent is granted. According to the second hypothesis, the negative exogenous shock in the availability of financial resources following the EBA capital exercise is argued to have a *positive* impact on these inventive dimensions for the exposed firms based on their ex-ante lending shares towards EBA banks. Starting with the patent measure capturing the forward citations, the results of the above described three-fold model-specification are summarized in Table 4 below:

	Forward Citations	Forward Citations	Forward Citations
Treatment	0.103	0.104	-0.003
	(6.62)***	(6.68)***	(0.07)
Exposure	0.005	0.002	-0.004
	(0.44)	(0.16)	(0.45)
DiD-Estimator	0.030	0.026	0.031
	(1.62)	(1.40)	(1.72)*
Constant	0.093	0.039	-0.021
	(3.91)***	(1.50)	(0.29)
Micro Controls	YES	YES	YES
Industry Fixed Effects	NO	YES	YES
Macro Controls	NO	NO	YES
Country Fixed Effects	NO	NO	YES
Year Fixed Effects	NO	NO	YES
Adjusted R^2	.13	.14	.40
N	1492	1492	1450

Table 4 presents the firm-level regression results of the difference-in-difference model for the qualitative patent measure which records the patent forward citations in normalized terms in different model specifications. The sample consists of all firms in the intersection of Patstat, DealScan and Amadeus which are located in Austria, Belgium, Finland, France, Germany, the Netherlands, Sweden and the United Kingdom. The treatment is based on the execution of the European Capital Exercise vis-à-vis EBA banks, whereas the firms' exposure to the treatment is based on the ex-ante median split of their lending shares towards these banks. Micro controls include firms' logarithm of total assets, cash, equity, debt ratio, shareholder funds, net current assets, intangible as well as other fixed assets. Industry Fixed effects are based on the NACE Rev. 2 industry classification. Macro controls include measures on GDP per capita and GDP growth, balance of trade, labor productivity, R&D expenditures, a Financial Distress Indicator and a Financial Crisis Indicator for each of the countries. Details on the variables are depicted in subsection 8.1. Standard errors are adjusted for heteroscedasticity and clustered at firm level. Significance levels: * (p<0.10), ** (p<0.05), *** (p<0.01).

Consistently with the previous elaborations on the budgetary patent measures, the estimates on the parameter of interest β_3 are again highlighted in the framed box for the *qualitative* forward citation variable and contain the numerical outcomes on the DiD-Estimator which capture the treatment effect in the different model specifications. As previously described, the number of forward citations mirrors the technological importance of a patent for subsequent technologies, where higher outcomes were shown to indicate higher economic value of the underlying patented inventions. From Table 4 above, it can be seen that the estimated treatment effect regarding the forward citations is positive, however statistically insignificant in the baseline and the second specification, while it becomes statistically significant at the ten percent significance level in the most sophisticated model. Therefore, this result provides support for the second hypothesis according to which the negative shock in the availability of financial resources has a positive impact on the qualitative forward citation dimension with respect to the exposed firms. As previously described, the measure on the patents' forward citations is generated as a normalized index variable. Consequently, in terms of economic relevance, the estimation result on the treatment effect in the most sophisticated model specification indicates that the patents of the exposed firms receive about 3.1 percent more forward citations following the EBA capital exercise relative to the non-exposed firms. Besides this, it is interesting to note that the estimates on the exposure parameter are insignificant in all three specifications which indicates that there are no average permanent differences between the exposed and non-exposed firms with

	Patent Family Size	Patent Family Size	Patent Family Size
Treatment	0.007	0.006	0.072
	(1.22)	(1.06)	(2.26)**
Exposure	0.007	0.005	0.003
	(0.66)	(0.49)	(0.27)
DiD-Estimator	0.014	0.015	0.020
	(1.29)	(1.41)	(1.83)*
Constant	0.109	0.022	0.035
	(4.77)***	(0.86)	(0.60)
Micro Controls	YES	YES	YES
Industry Fixed Effects	NO	YES	YES
Macro Controls	NO	NO	YES
Country Fixed Effects	NO	NO	YES
Year Fixed Effects	NO	NO	YES
Adjusted R^2	.07	.09	.25
N	1942	1942	1857

Table 5 presents the firm-level regression results of the difference-in-difference model for the qualitative patent measure which records the patent family size in normalized terms in different model specifications. The sample consists of all firms in the intersection of Patstat, DealScan and Amadeus which are located in Austria, Belgium, Finland, France, Germany, the Netherlands, Sweden and the United Kingdom. The treatment is based on the execution of the European Capital Exercise vis-à-vis EBA banks, whereas the firms' exposure to the treatment is based on the ex-ante median split of their lending shares towards these banks. Micro controls include firms' logarithm of total assets, cash, equity, debt ratio, shareholder funds, net current assets, intangible as well as other fixed assets. Industry Fixed effects are based on the NACE Rev. 2 industry classification. Macro controls include measures on GDP per capita and GDP growth, balance of trade, labor productivity, R&D expenditures, a Financial Distress Indicator and a Financial Crisis Indicator for each of the countries. Details on the variables are depicted in subsection 8.1. Standard errors are adjusted for heteroscedasticity and clustered at firm level. Significance levels: * (p<0.10), ** (p<0.05), *** (p<0.01).

respect to the forward citations received of the patent which were filed by these firms. The estimates on the treatment, finally, capture the common time trend to the control and treatment groups which is positive and significant in the baseline and the second model and becomes insignificant in the last specification. Overall, these regression results regarding the qualitative forward citations are supportive for the second hypothesis of this paper.

In Table 5 above, analogous regression results are provided for the second qualitative patent measure, which relates to the geographical scope in terms of the number of patent office jurisdictions in which a particular patent seeks for protection and is referred to as the patent family size. As described in the preceding subsections, previous literature found that there is a positive relationship between patent value and the patent family size. From the regression results above, it can be inferred that the estimated treatment effect regarding the family size outcome is positive, however statistically insignificant in the baseline and the second specification, while it becomes statistically significant at the ten percent significance level in the most sophisticated model. Hence, this result provides further support for the second hypothesis of this paper. As the family size measure is also normalized, the estimation result on the treatment effect in the most sophisticated difference-in-difference model indicates that the patents of the exposed firms are characterized by on average 2 percent larger family sizes relative to the non-exposed firms following the EBA capital exercise. Apart from this this, the estimates on the exposure parameter are insignificant in all three specifications which indicates that there are no average permanent differences between the exposed and non-exposed firms with respect to their family size outcomes. The estimates on the treatment, finally, capture the common time trend to the control and treatment groups which is positive and significant in the most sophisticated specification. In summary, these results which refer to the patent family size measure are also supportive for the second hypothesis of this paper.

The next set of regression results refers to the third qualitative patent measure, i.e. the share of withdrawn patent applications. As described in prior parts of this paper, previous literature found that applicants tend to withdraw their applications when they perceive the expected profit of the potentially granted patent as too low in order to continue the application process. Furthermore, patent withdrawals were shown to often take place after patentees received a negative feedback by patent authorities regarding the patentability of the underlying invention. Consequently, withdrawals are argued to be negatively related to the underlying value of the patented invention. Based on these considerations, the regression results on the treatment effects in Table 6 below show that the DiD-estimators are negative and statistically significant in all three model specifications at the five percent significance level. In the light of the considerations from previous literature, these results provide support for the second hypothesis of this paper, as the exposed firms have lower withdrawal rates regarding their patent applications compared to the control group firms. More precisely, the estimation result on the treatment effect in the most sophisticated model specification indicates that the exposed firms have 5.2 percent lower patent withdrawal rates following the negative shock in the availability of financial resources in the course of the EBA capital exercise relative to the non-exposed firms. Besides this, it is worthwhile noting that the estimates on the exposure parameter are insignificant in all three specifications. This indicates that there are no average permanent differences between the exposed and non-exposed firms regarding the patent withdrawal rates. At last, the estimates on the treatment are insignificant in all three model specifications. Summing up, the regression results regarding the patent withdrawals measure provide further support for the second hypothesis of this paper.

	Patent Withdrawals	Patent Withdrawals	Patent Withdrawals
Treatment	-0.069	-0.063	-0.150
	(3.50)***	(3.08)***	(1.48)
Exposure	0.022	0.015	0.009
	(1.36)	(1.26)	(0.81)
DiD-Estimator	-0.060	-0.055	-0.052
	(2.32)**	(2.18)**	(2.11)**
Constant	0.034	0.895	1.091
	(0.74)	(26.91)***	(8.47)***
Micro Controls	YES	YES	YES
Industry Fixed Effects	NO	YES	YES
Macro Controls	NO	NO	YES
Country Fixed Effects	NO	NO	YES
Year Fixed Effects	NO	NO	YES
Adjusted R^2	.07	.21	.30
N	1917	1917	1835

Table 6 presents the firm-level regression results of the difference-in-difference model for the qualitative patent measure which records the patent withdrawals in normalized terms in different model specifications. The sample consists of all firms in the intersection of Patstat, DealScan and Amadeus which are located in Austria, Belgium, Finland, France, Germany, the Netherlands, Sweden and the United Kingdom. The treatment is based on the execution of the European Capital Exercise vis-à-vis EBA banks, whereas the firms' exposure to the treatment is based on the ex-ante median split of their lending shares towards these banks. Micro controls include firms' logarithm of total assets, cash, equity, debt ratio, shareholder funds, net current assets, intangible as well as other fixed assets. Industry Fixed effects are based on the NACE Rev. 2 industry classification. Macro controls include measures on GDP per capita and GDP growth, balance of trade, labor productivity, R&D expenditures, a Financial Distress Indicator and a Financial Crisis Indicator for each of the countries. Details on the variables are depicted in subsection 8.1. Standard errors are adjusted for heteroscedasticity and clustered at firm level. Significance levels: * (p<0.10), ** (p<0.05), *** (p<0.01).

The final set of regressions depicts the estimation results on the last qualitative patent measure which refers to the time lag until a patent is granted. As discussed above, previous literature argues that applicants try to speed up the grant procedure for their most valuable patents and finds an inverse relationship between the length of a patent grant and patent value. In the light of these considerations, the regression results on the treatment effects in Table 7 below show that the DiD-estimators are negative and statistically significant in all three model specifications at the five or ten percent significance level. Against the background of the lines of arguments from previous literature, these results provide further support for the second hypothesis of this paper, according to which the negative shock in the availability of financial resources has a positive impact on this qualitative dimension of the inventive outcome with respect to the exposed firms, as these firms have lower grant lag outcomes regarding their patent applications compared to the control group firms. As previously described, the measure on the patents' grant lag outcome is generated as a normalized index variable. Consequently, in terms of economic relevance, the estimation result on the treatment effect in the most sophisticated model specification indicates that the exposed firms have on average 5.2 percent lower grant lag durations following the negative shock in the availability of financial resources in the course

	Patent Grant Lag	Patent Grant Lag	Patent Grant Lag
Treatment	0.160	0.165	0.311
	(8.09)***	(8.41)***	(2.57)**
Exposure	-0.003	-0.003	0.001
	(0.15)	(0.16)	(0.05)
DiD-Estimator	-0.054	-0.061	-0.052
	(1.94)*	(2.26)**	(1.79)*
Constant	0.396	0.707	0.706
	(7.92)***	(9.04)***	(3.91)***
Micro Controls	YES	YES	YES
Industry Fixed Effects	NO	YES	YES
Macro Controls	NO	NO	YES
Country Fixed Effects	NO	NO	YES
Year Fixed Effects	NO	NO	YES
Adjusted R^2	.11	.21	.27
N	1666	1666	1609

Table 7 presents the firm-level regression results of the difference-in-difference model for the qualitative patent measure which records the patent grant lag in normalized terms in different model specifications. The sample consists of all firms in the intersection of Patstat, DealScan and Amadeus which are located in Austria, Belgium, Finland, France, Germany, the Netherlands, Sweden and the United Kingdom. The treatment is based on the execution of the European Capital Exercise vis-à-vis EBA banks, whereas the firms' exposure to the treatment is based on the ex-ante median split of their lending shares towards these banks. Micro controls include firms' logarithm of total assets, cash, equity, debt ratio, shareholder funds, net current assets, intangible as well as other fixed assets. Industry Fixed effects are based on the NACE Rev. 2 industry classification. Macro controls include measures on GDP per capita and GDP growth, balance of trade, labor productivity, R&D expenditures, a Financial Distress Indicator and a Financial Crisis Indicator for each of the countries. Details on the variables are depicted in subsection 8.1. Standard errors are adjusted for heteroscedasticity and clustered at firm level. Significance levels: * (p<0.10), ** (p<0.05), *** (p<0.01).

of the EBA capital exercise relative to the non-exposed firms. Apart from that, the estimates on the exposure parameter are insignificant in all three specifications. This indicates that there are no average permanent differences between the exposed and non-exposed firms regarding the patent withdrawal rates. Finally, the estimates on the treatment capture the common time trend to these firm-groups which are positive and significant in all three model specifications. Therefore, also the regression results regarding the last patent grant lag measure provide further support for the second hypothesis of this paper.

Summarizing the empirical results on both, the budgetary as well as the qualitative patent measures, the findings from the most sophisticated difference-in-difference model specifications confirm the two hypotheses of this paper. The conventional view that a negative shock in the availability of financial resources affects *budgetary* dimensions of firms' inventive outcomes negatively is supported by the patent measure capturing the number of firms' filed patent applications and is, therefore, in line with the first hypothesis of this paper. Furthermore, the second hypothesis, according to which the negative shock in the availability of financial resources has a positive impact on qualitative dimensions of firms' inventive activities is backed by the empirical findings with respect to the qualitative patent measures that relate to the patents' forward citations, their family sizes, the patent withdrawals as well as the durations of the patent grant. In a final step, the empirical estimation results on both, budgetary and qualitative patent measures are jointly displayed in Table 8 in their most sophisticated difference-in-difference model specifications in order conclusively point to the twofold findings which support the twofold hypotheses from this paper:

	Patent Applications	Patent Claims	Forward Citations	Patent Family Size	Patent Withdrawals	Patent Grant Lag
Treatment	0.021	-0.045	-0.003	0.072	-0.150	0.311
	(1.15)	(0.88)	(0.07)	(2.26)**	(1.48)	(2.57)**
Exposure	0.008	0.009	-0.004	0.003	0.009	0.001
	(0.96)	(0.60)	(0.45)	(0.27)	(0.81)	(0.05)
DiD-Estimator	-0.014	-0.007	0.031	0.020	-0.052	-0.052
	(2.15)**	(0.26)	(1.72)*	(1.83)*	(2.11)**	(1.79)*
Constant	0.016	0.462	-0.021	0.035	1.091	0.706
	(0.34)	(1.48)	(0.29)	(0.60)	(8.47)***	(3.91)***
Micro Controls	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Macro Controls	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Adjusted R^2	.37	.25	.40	.25	.30	.27
N	1857	1841	1450	1857	1835	1609

Table 8 presents the firm-level regression results for the most sophisticated difference-in-difference model including micro controls, macro controls, industry fixed effects, country fixed effects and year fixed effects for both, the budgetary and the qualitative patent measures. The sample consists of all firms in the intersection of Patstat, DealScan and Amadeus which are located in Austria, Belgium, Finland, France, Germany, the Netherlands, Sweden and the United Kingdom. The treatment is based on the execution of the European Capital Exercise vis-à-vis EBA banks, whereas the firms' exposure to the treatment is based on the ex-ante median split of their lending shares towards these banks. Micro controls include firms' logarithm of total assets, cash, equity, debt ratio, shareholder funds, net current assets, intangible as well as other fixed assets. Industry Fixed effects are based on the NACE Rev. 2 industry classification. Macro controls include measures on GDP per capita and GDP growth, balance of trade, labor productivity, R&D expenditures, a Financial Distress Indicator and a Financial Crisis Indicator for each of the countries. Details on the variables are depicted in subsection 8.1. Standard errors are adjusted for heteroscedasticity and clustered at firm level. Significance levels: * (p<0.10), ** (p<0.05), *** (p<0.01).

Building on these findings, further regression analyses are provided in the next sections which aim at investigating the validity of the above results in more detail in the light of the model specifications that were utilized in the empirical part of this paper so far.

6.1 Robustness Tests

The empirical investigations so far provide robust estimation results in the three difference-in-difference model specifications on the treatment effect for the discussed budgetary and qualitative patent measures regarding the impact of the negative shock in the availability of financial resources in the course of the EBA capital exercise. More precisely, for the individual patent measures considered, the signs and dimensions on the DiD-estimators remain overall unchanged in the different regression models and are, in particular, statistically significant in the most sophisticated specification, as depicted in Table 8 above. Based on these results, in a next step further robustness tests are included in the analysis.

In the empirical part of this paper so far, it is assumed that firms' inventive outcomes are affected with a one period time lag following the negative exogenous shock in the availability of their financial resources as a result of the EBA capital exercise. The rationale for this consideration is that it takes time for inventive outcomes which are capital intensive and, therefore, dependent on the availability of financial resources to react to negative shocks in the availability of these resources. If this is indeed the case, it is expected that the derived estimates on the treatment effect should fade away and become insignificant if the above established lag structure regarding the dependent patent measures is removed in the difference-in-difference model. Following this, the subsequent regressions are based on the same, most sophisticated model from above, except that in these specifications the patent measures are not lagged by one period as in the baseline model, but rather refer to the same period as the remaining variables, including the indicator on the treatment, the interaction term capturing the treatment effect as well as the remaining control variables included in the most sophisticated model specification. The estimation results for this model specification are provided in Table 9 below:

	Patent Applications	Patent Claims	Forward Citations	Patent Family Size	Patent Withdrawals	Patent Grant Lag
Treatment	0.021	-0.036	0.002	0.039	-0.031	0.238
	(1.45)	(0.71)	(0.05)	(1.58)	(0.62)	(2.54)**
Exposure	0.006	0.009	0.001	0.004	0.005	0.003
	(0.79)	(0.65)	(0.12)	(0.34)	(0.49)	(0.19)
DiD-Estimator	-0.010	0.019	0.016	0.008	-0.010	-0.049
	(1.62)	(0.74)	(1.39)	(0.66)	(0.38)	(0.80)
Constant	0.194	0.440	-0.062	-0.054	0.730	0.908
	(1.62)	(1.52)	(0.82)	(0.34)	(2.28)**	(6.29)***
Micro Controls	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Macro Controls	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Adjusted R^2	.32	.25	.46	.25	.40	.30
N	2001	1990	1698	2001	1985	1840

Table 9 presents the robustness test firm-level regression results for the most sophisticated difference-in-difference model including micro controls, macro controls, industry fixed effects, country fixed effects and year fixed effects for the non-lagged budgetary and the qualitative patent measures. The sample consists of all firms in the intersection of Patstat, DealScan and Amadeus which are located in Austria, Belgium, Finland, France, Germany, the Netherlands, Sweden and the United Kingdom. The treatment is based on the execution of the European Capital Exercise vis-à-vis EBA banks, whereas the firms' exposure to the treatment is based on the ex-ante median split of their lending shares towards these banks. Micro controls include firms' logarithm of total assets, cash, equity, debt ratio, shareholder funds, net current assets, intangible as well as other fixed assets. Industry Fixed effects are based on the NACE Rev. 2 industry classification. Macro controls include measures on GDP per capita and GDP growth, balance of trade, labor productivity, R&D expenditures, a Financial Distress and a Financial Crisis Indicator for each of the countries. Details on the variables are depicted in subsection 8.1. Standard errors are adjusted for heteroscedasticity and clustered at firm level. Significance levels: * (p<0.10), ** (p<0.05), *** (p<0.01).

The estimation results on the parameter of interest are again highlighted in the framed box and include the numerical outcomes on the DiD-Estimator, which captures the treatment effect in the different specifications in the difference-in-difference model with non-lagged patent measures. In comparison to the estimation results from Table 8 above, it can be seen that the difference-in-difference parameter became insignificant in all of the patent measures. Consequently, this result provides support for the consideration that it takes time for inventive outcomes which are capital intensive and to react to negative shocks in the availability of these resources. Therefore, these regression results provide support for the validity of the chosen empirical model which is based on the patent measures that are lagged by one period. Apart from this, it is also worthwhile noting that the estimates on the exposure parameter are again insignificant in all three specifications, which indicates that there are no average permanent differences between the exposed and non-exposed firms regarding the number of patent applications filed by these firms. The estimates on the treatment, finally, capture the common time trend to the control and treatment groups which is insignificant for all patent measures apart from the grant lag variable.

By analogy, the second robustness test shifts the time dimension of the patent measures in the opposite direction, thereby analyzing the same, most sophisticated model from above, except that the patent measures are lagged by *two* periods relative to the remaining regression variables, including the indicator on the treatment, the interaction term capturing the treatment effect as well as the remaining control variables. The rationale for this proceeding is that, given that it takes time for inventory outcomes to react to the negative shock in the availability of financial resources following the EBA capital exercise, the derived estimates on the treatment effect should not fade away completely as in the first robustness test from Table 9 above if the lag structure on the patent measures is increased by one period. In order to evaluate this line of thought, the estimation results for the second robustness test are depicted below:

	Patent Applications	Patent Claims	Forward Citations	Patent Family Size	Patent Withdrawals	Patent Grant Lag
Treatment	0.027	-0.055	0.041	-0.051	0.061	0.162
	(1.64)	(1.11)	(0.74)	(1.92)*	(1.23)	(1.24)
Exposure	0.008	0.008	0.001	0.006	0.009	-0.011
	(0.85)	(0.50)	(0.06)	(0.44)	(0.72)	(0.69)
DiD Estimator	-0.013	-0.012	0.013	0.004	-0.063	-0.007
	(1.71)*	(0.39)	(0.46)	(0.45)	(2.39)**	(0.18)
Constant	0.061	0.407	-0.225	0.117	0.526	0.806
	(0.92)	(1.25)	(1.41)	(0.79)	(3.45)***	(7.93)***
Micro Controls	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Macro Controls	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Adjusted R^2	.35	.25	.40	.24	.30	.28
N	1637	1629	1300	1637	1620	1435

Table 10 presents the robustness test firm-level regression results for the most sophisticated difference-in-difference model including micro controls, macro controls, industry fixed effects, country fixed effects and year fixed effects for the 2 year lagged budgetary and the qualitative patent measures. The sample consists of all firms in the intersection of Patstat, DealScan and Amadeus which are located in Austria, Belgium, Finland, France, Germany, the Netherlands, Sweden and the United Kingdom. The treatment is based on the execution of the European Capital Exercise vis-à-vis EBA banks, whereas the firms' exposure to the treatment is based on the ex-ante median split of their lending shares towards these banks. Micro controls include firms' logarithm of total assets, cash, equity, debt ratio, shareholder funds, net current assets, intangible as well as other fixed assets. Industry Fixed effects are based on the NACE Rev. 2 industry classification. Macro controls include measures on GDP per capita and GDP growth, balance of trade, labor productivity, R&D expenditures, a Financial Distress and a Financial Crisis Indicator for each of the countries. Details on the variables are depicted in subsection 8.1. Standard errors are adjusted for heteroscedasticity and clustered at firm level. Significance levels: * (p<0.10), ** (p<0.05), *** (p<0.01).

In contrast to the regression results from Table 9, it can be seen that the difference-in-difference estimator in Table 10 remains significant regarding the budgetary patent measure which refers to the number of filed patent applications as well as regarding the qualitative patent measure which refers to the withdrawals.

Besides this, the DiD-estimators on all patent measures point in the same direction as in the main part of the paper, such that the second robustness test provides further support for the validity of the chosen empirical model. These test results, therefore, increase confidence that the established results indeed capture the impact of the EBA capital exercise shock on different dimensions of firms' patented inventions.

The final regression set refers to an analysis which goes beyond the specification of varying lag structures regarding the examined patent measures in the most sophisticated difference-in-difference model. The purpose of this section lies in testing the validity of the estimation results in context of the chosen identification strategy. If the findings so far indeed relate to the impact of the negative shock in the availability of financial resources following the EBA capital exercise, the timing of the treatment regarding the above-described exposure classification is vitally important in order to obtain valid outcomes that do not depict spurious estimation results on the treatment effect. The identification strategy in this paper relates to differences in firms' exposures in their ex ante lending shares towards the EBA banks, which decreased their available lending resources in the course of this capital exercise. Based on this consideration, the following regressions contain the estimation results of a placebo test, which is based on an alternative timing of the treatment and which pretends that the EBA capital exercise was not introduced in 2011, but rather in the year of the outbreak of the financial crisis in 2007.

	Patent Applications	Patent Claims	Forward Citations	Patent Family Size	Patent Withdrawals	Patent Grant Lag
Treatment (Crisis)	0.003	-0.064	-0.032	0.132	-0.065	0.126
	(0.18)	(1.10)	(0.61)	(4.03)***	(1.02)	(1.39)
Exposure	0.011	0.003	-0.008	0.006	0.011	-0.000
	(1.35)	(0.15)	(0.98)	(0.42)	(0.60)	(0.01)
DiD (Placebo)	-0.009	0.008	0.014	-0.000	-0.015	-0.009
	(0.95)	(0.37)	(1.36)	(0.05)	(0.63)	(0.38)
Constant	0.010	0.555	-0.016	0.037	1.073	0.739
	(0.21)	(1.99)**	(0.21)	(0.64)	(8.03)***	(4.15)***
Micro Controls	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Macro Controls	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Adjusted R^2	.37	.25	.40	.25	.30	.27
N	1857	1841	1450	1857	1835	1609

Table 11 presents the placebo test firm-level regression results for the most sophisticated difference-in-difference model including micro controls, macro controls, industry fixed effects, country fixed effects and year fixed effects for budgetary and the qualitative patent measures. The sample consists of all firms in the intersection of Patstat, DealScan and Amadeus which are located in Austria, Belgium, Finland, France, Germany, the Netherlands, Sweden and the United Kingdom. The treatment is based on the execution of the European Capital Exercise vis-à-vis EBA banks, whereas the firms' exposure to the treatment is based on the ex-ante median split of their lending shares towards these banks. Micro controls include firms' logarithm of total assets, cash, equity, debt ratio, shareholder funds, net current assets, intangible as well as other fixed assets. Industry Fixed effects are based on the NACE Rev. 2 industry classification. Macro controls include measures on GDP per capita and GDP growth, balance of trade, labor productivity, R&D expenditures, a Financial Distress and a Financial Crisis Indicator for each of the countries. Details on the variables are depicted in subsection 8.1. Standard errors are adjusted for heteroscedasticity and clustered at firm level. Significance levels: * (p<0.10), ** (p<0.05), *** (p<0.01).

The financial crisis itself had arguably an overall negative impact on the availability of financial lending resources, which however did not only affect banks that participated at the EBA capital exercise but rather the whole banking sector in Europe and across the world. Therefore, if the outbreak of the recent financial crisis was chosen as the treatment, while the exposure classification was still based on the firms' ex ante lending shares towards the EBA banks as of 2010, the treatment effects should become insignificant in the placebo specification of the most sophisticated difference-in-difference model. This is the case because the outbreak of the recent financial crisis is likely unrelated to an exposure classification that refers to firms' EBA bank lending shares from 2010 and, therefore, to a scheme which utilizes firms' lending data as of three years after the outbreak of the recent financial crisis. In fact, the estimation results on the treatment effects from Table 11 above are statistically insignificant with respect to all patent measures considered. Based on the placebo treatment, which relates to the outbreak of the recent financial crisis, the exposed firms are, therefore, not affected differently than the non-exposed firms in terms of their inventory outcomes. Consequently, this result strengthens the notion that the treatment effect is indeed related to the true treatment, namely the conduction of the EBA capital exercise. In summary, this results thus provides further support to the effect that the previous analyses indeed capture the true causal effect of the negative shock in the availability of financial resources following the EBA capital exercise on the numerous dimensions related to firms' inventive activities based on the ex-ante differences of firms' lending shares towards the EBA banks.

7 Conclusion

The paper at hand analyzed the impact of decreases in available financial resources on budgetary as well as qualitative dimensions of firms' inventive activities which are related to their patenting activities. For this purpose, the European Capital Exercise, which required a subset of European banks to substantially increase their capital ratios, provided the basis for a quasi-natural experiment which was utilized in the empirical part of the paper in an difference-in-difference regression setup in an European context.

Previous literature showed that EBA banks, i.e. those banks which were included in the capital exercise, increased their capital positions mainly by a substantial reduction in outstanding syndicated customer loans. Based on these considerations, firms were classified as being exposed to these negative consequences of the EBA capital exercise depending on their ex ante lending shares towards the EBA banks. Building on this exposure classification, multi-fold empirical analyses were conducted which aimed at investigating the impact of the negative shock in the availability of financial resources followed by the EBA capital exercise on different dimensions of firms' inventive outcomes. For this purpose, a novel, self-generated dataset was utilized which contains multi-layered information on firms' inventive activities which are derived from the Patstat database. These information are complemented by information on firm-bank loan data from Dealscan as well as firm financial data from Amadeus.

Building on this unique, self-generated dataset, the empirical results of this paper support the 'less finance - less innovation' view. Higher bank capital requirements resulting in lower financial resources available for firm lending activities lead to less firm-level inventive activity in terms of budgetary patent measures, such as the number of filed patent applications and the amount of claims included in the patented documents. Qualitative dimensions of patented firm inventions, such as forward citations, patent family sizes, patent withdrawals and patent grant durations, on the other hand, are affected positively and therefore support 'less finance - better innovation' considerations. In order to understand these findings in a more profound way, further research is needed. In particular, different dimensions of firms' lending relationships to EBA banks provide potentially deeper insights regarding the underlying channels that drive the above-described findings. Besides this, future research should also consider differences in firms' credit constraints and, therefore, variations in firms' demand for capital. In summary, the findings from this paper, serve as a starting point for future research which aims at analyzing the impact of the availability of financial recourses and firms' inventive outcomes in a European setup in more detail.

8 Appendix

8.1 Generated Variables - Details

Patent Measures	
Variable	*Definition*
Patent Claims	$\text{claims}_p = n_p^{\text{claims}}$: $n \in \{\text{claim}_1, \ldots \text{claim}_{i}, \ \text{claim}_j, \ldots, \text{claim}_n\}$ & $\text{claim}_i \neq \text{claim}_j$
Forward Citations	$\text{forward citations}_p = \sum_{t=T}^{T+5} \sum_{j \in Q(t)} C_{p,q}$
Family Size	$\text{family size}_p = n_p^{\text{jur}}$: $n \in \{\text{jur}_1, \ldots \text{jur}_{a}, \ \text{jur}_b, \ldots, \text{jur}_J\}$ & $\text{jur}_a \neq \text{jur}_b$
Patent Withdrawal	$\text{withdrawal}_p = I_p \in 0,1$; 1 if patent p withdrawn by patentee; 0 else.
Grant Lag	$\text{grant lag}_p = \Delta t(\text{application filing date}_p \text{ ; grant date}_p)$
Firm-Level Financials	
Variable	*Definition*
ln(Assets)	Natural logarithm of total assets
Cash Ratio	$\frac{\text{Cash}}{\text{Total Assets}}$
Debt Ratio	$\frac{\text{Current+Non-Current Liabilities}}{\text{Total Assets}}$
EBITDA/ Assets	$\frac{\text{EBITDA}}{\text{Total Assets}}$
Equity Ratio	$\frac{\text{Equity}}{\text{Total Assets}}$
Macro-Level Variables	
Variable	*Definition*
Balance of Trade	Imports – Exports of goods and services
CLIFS	Country-Level Index of Financial Distress (ECB)
Crisis	Indicator variable equal to one for the period of a banking crisis based on Laeven & Valencia (2013)
GDP per Capita (GDP	$\frac{\text{Total GDP}}{\text{Total Population}}$
GDP per Capita Growth	$\frac{\text{GDP per capita}_t \text{- GDP per capita}_{t-1}}{\text{GDP per capita}_{t-1}}$
Labor Productivity	$\frac{\text{GDP}}{\text{hours worked}}$

Table A1 contains the definitions on the generated variables which were utilized in the empirical part of this paper, either in the descriptive analyses or in the regression analyses of this paper. Regarding the patent measures, the definitions are provided on individual patent level basis, *p*. The forward citations measure refers to a patent filed in year t=T, while Q(t) refers to the set of all patent applications q filed in year t and $C_{p,q}$ refers to a dummy variable which equals 1 if patent q cites patent p and equals zero otherwise. Regarding the family size measure, the *jur* indicator relates to distinct patent office jurisdictions in which a particular patent seeks for protection. While many of the measures are time invariant by construction, corresponding firm-level patent measures may vary over time as firms file numerous patents over time with diverse individual patent measure outcomes. Based on these considerations, time-variant patent measures on firm-level basis can be generated and utilized in the firm-level regression analyses. The patent measures are generated as normalized variables by means of dividing the initial results by the maximum score obtained in the same year and technology field cohort over a 98% winsorized distribution in order to deal with technological fluctuations, spurious outliers as well as to adjust for potential institutional changes, for instance in patent office policies. Details on patent measure specific evolvements over time, industry and firm countries as well as discussions on associated structural issues in context of patents filed by European firms can be found in Krzyzanowski (2019). In order to reduce the potential for distortion which may be caused by spurious outliers, the variables depicted below are constructed over a 98% winsorized distribution, i.e. indicators below the 1st percentile are transformed into values corresponding to the 1st percentile and those indicators above the 99th percentile are set to the 99th percentile.

8.2 List of Banks included in EBA Capital Exercise

Bank	**Country**
Erste Group Bank AG	Austria
Raiffeisen Zentralbank Österreich AG	Austria
KBC Bank	Belgium
Bank of Cyprus Public Co. Ltd.	Cyprus
Cyprus Popular Bank Public Co. Ltd.	Cyprus
Danske Bank	Denmark
Jyske Bank	Denmark
Nykredit	Denmark
Sydbank	Denmark
OP-Pohjola Group	Finland
BNP Paribas	France
BPCE	France
Credit Agricole	France
Societe Generale	France
Bayerische Landesbank	Germany
Commerzbank AG	Germany
DekaBank Deutsche Girozentrale	Germany
Deutsche Bank AG	Germany
DZ Bank AG DT.-Zentral-Genossenschaftsbank	Germany
HDH Nordbank AG	Germany
Hypo Real Estate Holding AG	Germany
Landesbank Baden-Württemberg	Germany
Landesbank Berlin AG	Germany
Landesbank Hessen-Thüringen Girozentrale	Germany
Norddeutsche Landesbank Girozentrale	Germany
Westdeutsche Genossenschafts-Zentralbank AG	Germany
OTP Bank Nyrt.	Hungary
Allied Irish Banks, Plc	Ireland
Bank of Ireland	Ireland
Irish Life and Permanent	Ireland
Banca Monte dei Paschi di Siena S.p.A.	Italy
Banco Populare – S.C.	Italy
Intesa Sanpaolo S.p.A.	Italy
Unicredit S.p.A.	Italy
Unione di Banche Italiane SCPA	Italy
Banque et Caisse d'Epargne de l'Etat	Luxembourg
Bank of Valletta (BOV)	Malta
ABN AMRO Bank NV	Netherlands
ING Bank NV	Netherlands
Rabobank Nederland	Netherlands
SNS Bank NV	Netherlands

DNB NOR Bank ASA	Norway
Powszechna Kasa Oszczednosci Bank Polski S.A.	Poland
Banco BPI SA	Portugal
Banco Comercial Português S.A.	Portugal
Caixa Geral de Depositos S.A.	Portugal
Espirito Santo Financial Group S.A.	Portugal
Nova Kreditna Banka Maribor d.d.	Slovenia
Nova Ljubljanska Banka d.d.	Slovenia
Banco Bilbao Vizcaya Argentaria S.A.	Spain
Banco Popular Español S.A.	Spain
Banco Santander S.A.	Spain
Caja de Ahorros y Pensiones de Barcelona	Spain
Nordea Bank AB	Sweden
Skandinaviska Enskilda Banken AB	Sweden
Svenska Handelsbanken AB	Sweden
Swedbank AB	Sweden
Barclays plc	United Kingdom
HSBC Holding plc	United Kingdom
Lloyds Banking Group plc	United Kingdom
Royal Bank of Scotland Group plc	United Kingdom

Table A2 contains the list of all banks which were included in the EBA capital exercise in 2011. For more details see *https://eba.europa.eu/risk-analysis-and-data/eu-capital-exercise/final-results.*

8.3 Exposed vs. Non-Exposed Firms

Descriptive Statistics – Exposed Firms vs. Non-Exposed Firms

		Total Assets (mn)	Debt Ratio	Equity Ratio	EBITDA/Assets Ratio	Cash Ratio
	Mean	318	0.60	0.39	0.12	0.07
	p25	82	0.50	0.28	0.06	0.01
Exposed Firms	Median	241	0.60	0.40	0.11	0.05
	p75	467	0.72	0.50	0.16	0.10
	Std. Dev.	282	0.20	0.19	0.08	0.09
	Mean	284	0.61	0.40	0.12	0.06
	p25	55	0.46	0.30	0.06	0.01
Non-Exposed Firms	Median	207	0.61	0.39	0.12	0.04
	p75	444	0.70	0.54	0.15	0.07
	Std. Dev	265	0.20	0.19	0.08	0.08
Diff.		34	-0.003	-0.004	0.004	0.01
P-Value	*(diff = 0)*	*0.01*	*0.58*	*0.39*	*0.14*	*0*

Table A3

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Deeper Pockets, Better Inventions?
Evidence from Financial Market Integration*

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Abstract

This paper examines the impact of improved access to funding on firm-level patenting regarding a quantity-quality tradeoff. I exploit exogenous variation from the staggered introduction of major amendments to EU law to show that a relaxation of financing constraints induces the average firm to file more patents which are, however, of lower technological quality, market value, and impact on subsequent inventions. These results are mainly driven by firms with ex ante low patenting activities, in line with a disciplining effect of financing constraints. My results provide novel insights on the role of financial resources for firm-level inventions against the background of a recent political agenda.

JEL Classification: D04; D22; F36; O31
Keywords: Patents, Financial constraints, Quality of Innovation, Financing Innovation

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1 Introduction

A conventional perception is that greater availability of financial resources enhances firm-level inventive activities: it induces higher spending on R&D (Brown *et al.* 2009, Hall and Lerner 2010), strengthens long-term research investments (Aghion *et al.* 2010), and increases patent filings (Chava *et al.* 2013). In line with this idea, both policymakers and academics stress the importance of facilitating access to funding particularly for financially constrained, innovative firms. Contrasting this, research indicates that increased funding or lower inventing costs might actually harm the *quality* of inventive activities. For example, financing constraints can act as a disciplining device inducing innovative efficiency on an individual (Ederer and Manso 2013), governmental (Gibbert and Scranton 2009), or firm level (Almeida *et al.* 2017). In the context of patenting, de Rassenfosse and Jaffe (2018) show that a substantial increase in filing costs at the U.S. Patent and Trademark Office during the 1980s effectively crowded out low quality applications.

A better understanding of the relationship between funding and inventions' quality is of particular relevance. First, qualitative characteristics of inventions relate to pervasiveness and the potential to create value more strongly as compared to quantitative measures, such as R&D expenses or patent counts (Harhoff and Wagner 2009, Raiteri 2018). Second, enhancing the quality of invented output helps firms to avoid market inefficiencies (Squicciarini *et al.* 2013) and increases their probability of survival (Hall and Harhoff 2012). In contrast, a lack of technological quality may trigger market failures which harm growth and employment (Hall *et al.* 2004).

Against this background, the question arises whether the impact of funding on inventive activities is as single-sided as commonly suggested. More specifically, one should ask whether there is a tradeoff between quantitative and qualitative dimensions of firms' inventive activities. Does improved access to funding indeed affect qualitative characteristics of firm-level inventions and, if so, what drives these results?

Evidence regarding these questions is scarce. My analysis attempts to fill this gap by empirically investigating whether and how an exogenous improvement in the access to funding translates to qualitative characteristics of patented inventions.[1] My results confirm the notion of a multilayered impact and an overall quantity-quality tradeoff of funding on inventive output. Relaxing firms' financing constraints and the subsequently increased use of external debt causes firms to file more patents but also alters the types of patents filed. On average, firms which experience this positive exogenous shift file patents of lower quality and value. Moreover, respective firms adjust their patenting strategy towards protecting more incremental inventions. These effects are heterogenous across firms. Results are driven by firms that have relatively low ex ante patenting activities. These findings underline both the general importance of funding for enhancing inventive activities as well as the potentially disciplining effect of financing constraints for certain firms.

Establishing a causal relationship between the access to funding and inventive activities is non-trivial. Reverse causality and endogeneity concerns are apparent issues. Rather than financing constraints affecting inventive activities, firms' inventive output also affects their use of financial resources (e.g. Kerr and Nanda 2015, Mann 2018). In addition, there might be unobserved simultaneous factors, such as general invention trends, which jointly drive patenting behavior. Aside of panel econometric techniques, my analysis therefore builds on a quasi-experimental setup that helps isolating the causal relation between finance and patenting. I exploit a major policy initiative, the Financial Services Action Plan (FSAP), in the European Union (EU) during the early 2000s as an identifying event. The market reform entails the staggered implementation

[1] Unlike other inventive activities, which are generally difficult to trace, the ex post analysis of patents allows precise quantification along multiple dimensions. I consider the technological quality and market value as well as the degree of incrementality (which is a function of novelty, impact and scope) as relevant attributes of patents.

of legal amendments as an effort by the European Commission to enhance financial integration among EU member states. In particular, I draw on seven bank-related FSAP amendments as a traceable, exogenous source of variation in firms' legal environment affecting borrowing conditions across countries (Kalemli-Özcan *et al.* 2013). The bank lending channel thereby constitutes the link between funding and inventive activities. This is a promising venue, because my data set predominantly includes privately-held, small and medium-sized firms (i.e. 3.5 percent of sample firms are listed). Unlike large public firms, small private firms strongly depend on banks as a provider of external funding (Berger and Udell 2006).

For identification, I utilize both cross- and within-country heterogeneity in the data. Cross-country variation arises from the differences in timing of implementation dates in different member states. Further, I distinguish between affected and unaffected firms within countries by their degree of being financially constrained ex ante. Hence, my identifying assumption is that the FSAP amendments have a pronounced positive effect on constrained firms' access to funding. To illustrate the validity of this, my analysis shows that financial market harmonization reduces interest burdens for affected firms and thereby enhances their debt capacity. Comparing pre- and post-integration levels (i.e. after an average of four to five years), interest charges decrease on average about 30 percent for the median firm, whereas bank loan to asset ratios of respective firms increase by 27 percent. In contrast, no significant changes in interest charges and loan ratios are observed for ex ante unconstrained firms.

In a series of analyses, I demonstate that results are robust to different model and estimation specifications. Importantly, I address concerns regarding the identifying assumption, namely, that the timing of financial integration is exogenous to patenting activities. Multiple analyses on pre-trends and lagged effects cannot invalidate my findings. The same applies for several plausibility tests. For example, placebo events mimicking FSAP amendments fail to explain changes in both patenting and financing activities. Although omitted variable concerns can never be entirely ruled out, these analyses mitigate concerns about the causal interpretation of the results.

This study extends existing literature in several ways. First, I provide a novel perspective on the impact of funding on inventive output by investigating a whole set of value-relevant patenting dimensions. Most notably, I am able to draw a comprehensive picture on a tradeoff between the quantity as well as qualitative dimensions of patented inventions. Second, to the best of my knowledge, this study is the first of its kind that covers a representative sample of the European business landscape including mostly small, privately-owned businesses from multiple sectors, across several countries and years. By merging highly disaggregated patent information to firms' financial data, this unique data set allows me to pin down important heterogeneous effects across firms that identify specific determinants of the aforementioned effects. Third, by focusing on bank borrowing, I shed more light on a crucial channel for the relationship between finance and innovation. Thereby, I further extend the literature on financial constraints and their impact on real economic activities. Finally, my study delivers important findings regarding the limitations of policies focusing on monetary aspects. The prevalence of a quantity-quality tradeoff raises questions about the efficient use of research funds, while stressing the importance to consider qualitative dimensions in respective spending decisions.

The paper proceeds as follows. Section 2 relates my analysis to existing literature and thereby carves out the contributions of this paper. Section 3 defines patent measures and describes the data base. The institutional background on the identifying event and my empirical strategy are outlined in Section 4. Section 5 presents the empirical results. Section 6 concludes.

2 Related literature and contributions

A multitude of factors determines corporate inventions, such as competition (Aghion and Bolton 1992, Correa and Ornaghi 2014), organizational structure (Aghion *et al.* 2013), firm size (Audretsch and Elston 2002), human capital input (Del Canto and Gonzáles 1999), governmental support (Mazzucato 2013, Guerzoni and Raiteri 2015), and firms' legal environment (Chava *et al.* 2013, Comin and Nanda 2014). My work addresses - but is not limited to - three main areas of research that focus on the determinants of inventive activities from different angles: i) the availability of financial resources, ii) incentives to innovate, and iii) economic development.

First, my study relates to literature on finance as a key input factor of inventive activities. Unlike most other determinants of innovation, access to finance is relevant for virtually all firms (Coad *et al.* 2016). Several studies examine financing constraints and their impact on (investment in) inventive activities. In general, negative adverse shocks to the supply of external finance result in lower investment, if internal funding is not sufficiently available (Stiglitz and Weiss 1981, Holmström and Tirole 1997). This effect is more pronounced for firms with higher financing costs and a stronger dependence on external funding sources, such as firms engaged in research activities (Hall and Lerner 2010; Brown *et al.* 2012). Many empirical studies emphasize that innovative firms are distinctively responsive to changes in funding (e.g. Savignac 2006, Hoegl *et al.* 2008, Hottenrott and Peters 2012, Hall *et al.* 2016). A common conclusion is that alleviating financing constraints induces firms to invest more in research and development and thereby innovate more (Brown *et al.* 2009, Acharya and Xu 2017). Most existing studies focus on standard measures of innovation, such as productivity, spending on R&D, or the number of patents. Importantly, the applicability of these measures to adequately capture inventive performance is increasingly questioned (see Lerner and Seru (2017) for a detailed description).

Several characteristics of inventive activities go beyond the usual asymmetric information concerns of financing investments and place a special role on the actual source of finance. Firms' life-cycle stage thereby strongly determines which specific source is most appropriate, particularly in the case of innovation-intense firms. For example, young, start-up firms commonly lack internal funds to undertake research and development. Venture capitalists can overcome this issue by providing a combination of external capital, active involvement, and advice (Casamatta 2003). In contrast, relatively older firms potentially have more internal funds available to finance their activities. Further, they are more likely to provide assets as collateral. Most decisive to this analysis, recent findings highlight the relevance of external debt providers for inventive activities (Kerr and Nanda 2015, Acharya and Xu 2017), particularly the important role of banks (Robb and Robinson 2014, Chava *et al.* 2017, Mann 2018) even for young start-ups (Hirsch and Walz 2019). My analysis relates and extends this emerging strand of literature by providing new evidence on the important role of banks in financing inventive activities.

I contribute to a second main strand of literature that identifies agency issues to affect innovative behavior, in particular, potential mechanisms how funding influences inventive activities. A prominent venue in this regard are incentivizing effects of available funding, respectively its absence. For example, limited amounts of funding can serve as a disciplining device by enforcing managers to optimize on investment decisions. Thus, input resource constraints can lead to more efficient use of the existing set of deployable resources (Goldenberg *et al.* 2001, Moreau and Dahl 2005, Gibbert and Scranton 2009), whereas removing these constraints may trigger wasteful investments (Aghion *et al.* 2013).

Incentives also play an important role when it comes to the type of inventions that are generated. Literature of cognitive psychology argues that financially unconstrained agents habitually acquire inputs needed for solving well-known, previously experienced problems (Scopelliti *et al.* 2014). In economic literature Ederer and Manso (2013) find that monetarily incentivized inventors create more ideas but these ideas are typically less explorative. Contrasting this, other studies find that large R&D budgets can induce managers to conduct more risky, high-profile projects if they are imperfectly monitored (Almeida *et al.* 2017). In addition, monetary aspects shape qualitative features of inventive output also on a firm level. For example, Nanda and Rhodes-Kropf (2016) suggest that financial markets actively drive inventive behavior. In a theoretical framework, the authors illustrate that high-impact inventions require 'hot' financial markets to enable their initial financing, commercialization and diffusion. In a different study, Nanda and Nicholas (2014) empirically assess the role of financial resources in shaping firm-level inventions. The authors study the era of the Great Depression during 1929-1933 in the U.S. as an exogenous event, affecting inventive behavior via the funding channel. Their results suggest that the negative shock to the supply of finance caused patenting activities to decline significantly, both in quantitative and qualitative terms. Moreover, the authors find an adjustment towards more conservative, low risk - and reward - inventive activities.[2] In the specific context of patenting, de Rassenfosse and Jaffe (2018) show that changes in filing costs have an effect on the quality of patents. By studying the effect of the Patent Law Amendment Act of 1982 in the U.S., which significant raised patenting fees, the authors find a causal, subsequent reduction low-quality patents.

My analysis extends these findings along multiple dimensions. First, I confirm the relevance of financial resources as a necessary, though not sufficient, input for successful inventive activities. Second, I draw on an extensive set of patent characteristics, which allows me to separately analyze quality and market value measures as well as multiple meaningful patent characteristics. Third, I provide new insights on the effects of (relaxed) financing constraints on inventive characteristics by studying novel micro-data on finance and patenting activities on a firm-level. The breadth of my data set therefore enables me to paint a more complete picture of the topic by illustrating heterogeneous effects across firms.

Finally, my analysis also contributes to literature on the impact of economic development (La Porta *et al.* 1998, Levine 2005), specifically financial integration (Bertrand *et al.* 2007, Kerr and Nanda 2009), on real economic activities. Empirical literature investigates the impact of bank regulation from a de jure perspective on credit availability and credit quality. Bank deregulation is associated with an increased sensitivity of bank-lending decisions to firm performance (Stiroh and Strahan 2003). Integration potentially helps reducing entry barriers, improving access to finance (Cetorelli and Strahan 2006), and lowering interest rate spreads particularly for small firms (Guiso *et al.* 2006).

A group of studies is most closely related to my analysis and investigates the effect of bank deregulations in the United States during the 1980s and 1990s on firm-level inventions (Chava *et al.* 2013, Amore *et al.* 2013, Cornaggia *et al.* 2015). The authors assume intra- and interstate deregulations to affect the supply of credit exogenously by changes in the level of competition among banks. They univocally identified a positive relationship between the intensity of inventive activities and their access to funding. Similarly to other related literature the authors focus on standard measures of inventions. My analysis regards the effects on a broad set of value-relevant characteristics and types of inventions. I can therefore investigate the potential tradeoff between quantitative and qualitative aspects of patenting. To the best of my knowledge, my analysis is the first to specifically study multiple output dimensions of inventive activities against the

[2] Unlike in my investigation, which studies changes in the relative degree of being financially constrained, Nanda and Nicholas (2014) explore a setup which is marked by a full credit rationing. This helps to explain the drastic, negative impact and stresses the importance of financial resouces as a necessary input.

background of improved access to funding. Further, I examine a large number of predominantly small and medium-sized, privately-held firms located in various European countries for which the bank borrowing channel is of high importance.

3 Data and measurement

3.1 Measuring inventions

Resulting in legally protected property rights, patenting-related activities are well suited for ex-post analyses of firms' inventive behavior. Due to higher maintenance costs as compared to other types of documented intellectual property, such as trademarks or utility models, patents are a cost relevant factor for firms' business activities. A common approach for investigating firms' patenting activity is the assessment of quantitative measures. The number of patent applications reflects the actual level of inventive output disregarding any qualitative aspects.[3]

This analysis particularly focuses on patent quality, which can be defined as the size of the inventive step that is protected by a patent (de Rassenfosse and Jaffe 2018). Hence, with increasing quality the propensity of a patent to generate market demand should increase. This is because the size of the inventive step makes it (arguably) more difficult to invent around a patent and lengthens the monopoly period of the patentee. Thus, technological superiority may entail higher market demand. Approximations of patent quality are inherently value relevant as enhanced patent quality relates positively to market efficiencies, the probability of survival, growth, and employment (Hall *et al.* 2004, Hall and Harhoff 2012, Squicciarini *et al.* 2013).

First, I consider the number of forward citations received as well as the number of claims included in the patent application as dimensions describing the technological quality of a patent. A high number of citations resembles the influence a certain patent has on subsequent inventions. Higher quality patents can be expected of receiving a higher number of citations (de Rassenfosse and Jaffe 2017). In addition, the number of claims included in a patent application indicates the legally protected properties of an invention, which is positively correlated to patent quality Zuniga *et al.* 2009. The two measures are not only relevant in terms of technological quality but also positively related to the value generated by a patent ex post. In order to assess market value separately, I thus consider two measures which directly relate to the market value but are independent from patents' technological features. Firms have to separately pay maintenance fees in every EPC jurisdiction and every year to continue the life of their patent. Because this is very costly, only valuable patents will be renewed at multiple offices. The number of patent offices a patent is filed at as well as the number of patent renewals therefore proxy patents' market value without being directly related to their technological features (Schankerman and Pakes 1986, Harhoff *et al.* 2003).[4]

Second, my analysis also regards more general categories of patents: explorative and incremental patents. Explorative patents are characterized by higher risk but also higher impact, whereas incremental inventions are less risky and rather exploitative, marginal improvements. Both types are value-relevant in distinct ways. Exploitative inventions have groundbreaking potential, delivering high returns at high risk. At the meantime, incremental inventions are thought of generating minor, successive but steady improvements at relatively low risk (Henderson 1993). Table 1 sum-

[3]The four requirements for the patentability of an invention specifically do not address qualitative aspects. According to the European Patent Convention (EPC 1973, Art. 52(1)) patentability requires the invention i) to have a "*technical character*", ii) to be "*new*" and previously undisclosed, iii) to be distinguished by an "*inventive step*" not obvious to someone expert in that technology, and iv) to be "*susceptible of industrial application*".

[4]A brief discussion on the relationship between patent quality and value is provided in Appendix A.

marizes respective measures, while Appendix A elaborates on the patenting dimensions and their definitions in more detail.

- Insert Table 1 here -

3.2 Data sets and descriptives

My data set combines information on firm financials with patenting data. I obtain financial information from several historical copies of the Amadeus database. Patent information is extracted from EPO's PATSTAT database, which encompasses the universe of patenting activities on a highly granular level. Using the string-based matching algorithm proposed by Peruzzi *et al.* (2014) allows me to combine the two sources. I augment the data base with manually collected country-specific information on FSAP implementation dates as well as additional macro-level and industry-specific control variables.[5]

I restrict the sample to firms that have filed at least one patent throughout the sample period. I exclude data points with zero or negative total assets, firms that cannot be categorized in industry-classes, and firms from financial or public sectors. To avoid biased estimates, variables are truncated at the 1-, respectively 99-percentile, if necessary. The sample contains observations for the years 2000 until 2008, which avoids including potentially confounding factors that arise from the introduction of the Euro (1999) and the Financial Crisis (2009).[6] Foremost, this time range captures the implementation phase of the treatment, i.e. the FSAP implementation dates.

I initially regard the EU15 countries as potential sample countries, because the FSAP directives were targeted only at those EU member states of the late 1990s. However, due to missing information on several countries in the historical Amadeus copies, the Austria, Greece, Portugal, and Spain cannot be included. The final sample consists of 175,457 observations (36,840 firms) from ten different countries and incorporates information on 925,989 patents which are aggregated on a firm-year basis. All patent quality measures presented above are defined on individual patent basis and are normalized on a year-cohort basis, where cohort refers to firms with the same NACE Rev. 2 main category classification. Finally, I allow firms to enter and leave the database in order to avoid potential survivorship bias. On average each firm is observed 6.8 times. With a mean age of 26 years, firms are generally well established. More notably, only 3.5 percent of sample firms are listed corporations. My data therefore captures a representative fraction of the business landscape by including mostly small and medium-sized private firms.

Summary statistics show that patenting activities are heterogeneous both across and within countries. Table 2 displays the distribution of observations and patents filings across sample countries. With the exception of Italy (only 0.6 percent of all observations) the sample resembles the actual population of European firms. The table also illustrates that large countries (i.e. Germany, France, and Great Britain) are dominant patentees. The majority of patents (61.2 percent) are filed by firms in the manufacturing sector (see Table A1 in Appendix D for the sectoral distribution). Amongst others this sector comprises the subsectors machinery, pharmaceuticals, chemicals, and computers, which are known for their patenting intensity.

- Insert Table 2 here -

The final sample consists of 175,457 observations (36,840 firms) and incorporates information on 925,989 patents which are aggregated on a firm-year basis. All patent quality measures presented

[5]Data on country-specific macro controls are obtained from OECD's statistical database, OECD.Stats.
[6]In some model extensions, I additionally use data on the three years preceding this timeframe.

above are defined on individual patent basis and are normalized on a year-cohort basis, where cohort refers to firms with the same NACE Rev. 2 main category classification. Finally, I allow firms to enter and leave the database in order to avoid potential survivorship bias. On average each firm is observed 6.8 times. With a mean age of 26 years, firms are generally well established. More notably, only 3.5 percent of sample firms are listed corporations. My data therefore captures a representative fraction of the business landscape by including mostly small and medium-sized private firms.

- Insert Table 3 here -

Further, Table 3 displays that patenting activities also vary significantly across firms. While some companies file zero patents in a given year, others apply for almost 3,000 patents. Heterogeneity is also high in terms of the market value of patents, that is renewal rates and family size. Overall, the distribution of patents is notably skewed towards low impact patents, which is in line with previous observations (e.g. Gambardella *et al.* 2007). Incremental patents make up a large fraction among all patents (43.3 percent), whereas only a comparably small fraction of patents appears to have a high impact on subsequent inventions (5.2 percent) or can be considered as explorative (1.7 percent). Note that 55.0 percent of patents are neither incremental nor explorative, which results from my categorial classification scheme. Those patents can be considered as a benchmark group, whereas incremental patents are of particularly low impact and scope and explorative patents are especially impactful, respectively. Table A2 (Appendix D) reports the correlation matrix of the main patent variables. Some values are sizable by definition, because the patent type variables build on certain patent quality and value characteristics. Overall, descriptive statistics show that the sample comprises a representative set of patenting firms and industries in Europe.

4 Institutional background and empirical strategy

4.1 Financial Integration in Europe: The Financial Services Action Plan

Studying the relationship between financial resources and inventions entails obvious endogeneity concerns. To counter this, my analysis deploys European financial market integration as an exogenous source of variation in firms' legal environment. The key idea is that harmonization can be considered as a positive shift in the borrowing conditions, relaxing financing constraints of firms in affected EU member states throughout the 2000s.

Financial Services Action Plan (FSAP) constitutes this identifying event, which was officially issued by the European Commission in 1999. The prime strategic intention was to integrate financial markets within the European Union by further harmonizing its regulatory framework. The Commission aimed at developing the legislative framework along four objectives: a single EU wholesale market, open and secure retail banking and insurance markets, state-of-the-art prudential rules and supervision as well as advancing towards an optimal single financial market. Therefore, it assigned EU member states to implement 42 legislative amendments over a time span of six years. These amendments included 29 major pieces of legislation (27 EU Directives and 2 EU Regulations) in the fields of banking, capital markets, corporate law, payment systems, and corporate governance. My analysis considers seven distinct directives that affect the banking sector according to the Commission's report on the *Evaluation of the Economic Impacts of the FSAP* (Malcolm *et al.* 2009). Table A3 in Appendix D lists all FSAP Directives.

4.2 Quantifying financial integration

To quantify financial integration, I utilize manually collected data on the FSAP implementation dates for all sample countries. I construct a measure of de jure integration capturing the sequential implementation of relevant amendments, i.e. seven banking-related directives. The measure incorporates the country-weighted timing of the implementation of respective EU Directives. I thereby capture the notion that integration is a process of mutual adaptation. Based on this, I quantify financial integration as follows:

$$FI_{ct} = \frac{1}{7}\sum_{d=1}^{7}\left(D_{dtc} \times \frac{\sum\limits_{j\neq c} D_{dtj}}{14}\right) \quad \text{, with } D_{dtc} = \begin{cases} 1 \text{ if d is implemented in c at year t} \\ 0 \text{ otherwise} \end{cases} \quad , \qquad (1)$$

where variables D_{dtc} and D_{dtj} equal one, if one of the seven banking-related FSAP directives, $d \in [1, 7]$, is active during the year t in country c, or country j (with $c \neq j$) respectively, and zero otherwise. To introduce the multilateral dependence, this indicator variable is multiplied by the fraction of all other EU-15 members where the respective directive is active. The financial integration measure thus ranges between zero and one.[7] Figure 1 displays the evolution of the time varying and country specific FI_{ct} measure as defined in Equation (1) over time. Between 2000 and 2004, financial integration progresses relatively slow compared to the second phase between 2004 and 2008. This morrors that the magnitude of the measure is interdependent across countries, i.e. the mutual dependency of financial integration.

- Insert Figure 1 here -

The specific modeling of the measure mitigates endogeneity concerns for several reasons. First, EU Directives are considered non-anticipatory, because they become effective on an individual country-specific basis after passing domestic legislation (Kalemli-Özcan *et al.* 2010, 2013). The exact timing is thus unlikely to be anticipated, because implementation of these directives usually requires multiple years, varies considerably across member states, and does not occur based on an ex ante predefined dates. Second and related to this, because the original schedule of the FSAP was set in the late 1990s, implementation is unlikely to reflect market responses several years later (Christensen *et al.* 2016). Third, the implementation of respective directives is unilateral (i.e. domestic), whereas financial integration is a multilateral concept. My measurement accounts for this multilateral nature of financial integration as it weights the implementation of directives by mutual implementation of other EU members. Fourth, individual firms' actions might be related to certain country-specific initiatives, however, EU decisions are made on a supra-national level, which mitigates this concern (Schnabel and Seckinger 2019). Finally, FSAP Directives do not specifically target my outcome variables (i.e. patenting activities) by any means.[8]

Figure 2 shows the correlation between the integration index and different patent variables graphically. It plots the FI_{ct} measure on the horizontal axis and patenting filings (left plot) as well as the technological quality of patents, proxied by patent claims, (right plot) on the vertical axis in 25 equally sized bins. The graphs illustrate a positive correlation between the integration

[7] For example, in a three-country scenario, if country A implements all FSAP Directives but country B and C do not implement any directive, no integration would be reached. If county A and B adopted all respective laws, for these two countries FI_{ct} is equal to 0.5 and 0 for country C. Only in the case that all countries implement all directives at a given point in time, the measure equals 1.

[8] Appendix B contains further details on the empirical mechanism as well as a more elaborate reasoning on endogeneity concerns of the FSAP.

measure and the filing activities of firms. In constrast, integration relates negatively to the quality of patented inventions.[9]

- Insert Figure 2 here -

4.3 Identification and methodology

To assess the impact of relaxed financing constraints on patenting activities, I employ a generalized difference-in-difference (DID) approach (Angrist and Pischke 2008). The implementation of the seven banking-related FSAP Directives thereby constitutes a continuous treatment, affecting firms in all countries with different intensities at different points in time. Facilitated access to bank finance should particularly favor sample firms, because debt finance plays a relatively important role for smaller, research intensive firms (Kerr and Nanda 2015). For identification, I utilize heterogeneity in the sample in terms of firms' propensity to be affected by the legislative amendments. The improved access to funding is unlikely to have a uniform effect across all firms, i.e. changes in the supply of financing affects financially constrained firms disproportionally (Brown *et al.* 2009, Duchin *et al.* 2010). Hence, I distinguish between firms that are likely to be affected and those likely to be immune to the FSAP amendments by their degree of being financially constrained.

I draw on the logic of the S&A index, proposed by Hadlock and Pierce (2010) to quantify financing constraints. The index is an established measure, which predicts constraints as a function of firm size and age. I consider firms below, respectively above, the industry-year specific median of these two variables as financially constrained, respectively unconstrained.[10] It is important to note that literature questions the precision of globally applied measures of financial constraints (Farre-Mensa and Ljungqvist 2016). My approach is promising to cope with this issue, because it does not rely on marginal differences among scores but instead relies on a broad classification. Robustness tests additionally show that adjustments in the classification threshold do not change the interpretation of my results. Furthermore, estimates might be confounded, for example, if the variation in financial constraints is endogenous to unobserved variation in firm borrowing. I mitigate this concern by categorizing firms as affected exclusively based on their pre-integration specifications, i.e. averages for the years 2000-2002. Because the FSAP can be considered as an exogenous shock, firms properties regarding financial constraints should as well be exogenous as long as the integration process is not initiated.

As first descriptive evidence on the validity of this classification, Figure 3 recasts the binned scatterplots displayed in Figure 2 but split the sample according to affected and unaffected ('treatment' and 'control') firms. As expected, the respective correlations are more pronounced for ex ante financially constrained firms relative to unconstrained firms. This observation applies both regarding patent filings (left plot) as well as the technological quality of respective patents (right plot). Moreover, the scatterplots reveal two additional aspects. First, unlike in the typical differentiation among treatment and control firms, my categorization refers to a relative treatment. All firms are affected, but the 'treatment' group has a higher propensity to respond to the improved access to funding. Second, during the pre-treatment period both groups appear to follow a similar trend as the data points in the binned scatterplot overlap for low levels of the FI_{ct} measure in all specifications. I investigate particularly the latter aspect in more detail in the robustness section

[9]Similarly, recasting the binned scatterplot using the share of incremental patents shows a positive relationship with the integration index (Figure A1 in Appendix E), which implies a higher share of marginal inventions.

[10]Because this approach can be applied to small private firms, which make up the majority of sample firms, it is particularly suitable in my setup. Other common indices (e.g. Kaplan-Zingales or the Whited-Wu index) require information that are not available for this type of firm, such as dividend payments or bond market ratings.

of the empirical analysis. All findings from this exercise also apply to the share of incremental patents measured as Figure A2 (Appendix E) displays.

- Insert Figure 2 here -

My empirical strategy allows estimating the causal effect of relaxed financing constraints on inventive behavior regarding multiple patenting dimensions. Importantly, the panel structure of my data enables controlling for unobserved heterogeneity across firms and for country-specific time trends. Since lending generally follows a cyclical pattern (e.g. Ivashina and Scharfstein 2010), it is essential to account for time varying effects, such as differences in borrowing conditions.[11] The baseline model therefore reads as follows:

$$Invention_{it} = \beta_i + \beta_{ct} + \beta_1(FI_{ct-1} \times Exp_i) + \beta_2 X_{it} + \varepsilon_{it} \qquad , \tag{2}$$

where β_i and β_{ct} are firm- and country-year-fixed effects, respectively. X_{it} is a vector of control variables, as defined in Table A4 (Appendix D). $Invention_{it}$ resembles the inventive output of firm i in period t, which is either one of the seven patent measures defined in Table 1. Exp_i is a dummy variable based on my time-invariant classifications of whether a firm is ex ante financially constrained or not and therefore equals one of the firm is expected to be affected by the treatment or zero otherwise. The coefficient of interest, β_1, captures the (local) average treatment effect on the exposed firms and displays the causal effect of financial integration on firm-level patenting behavior for that particular subgroup. Note that perfect multicollinearity arises from including respective fixed effects and therefore omits the single regressors of the interaction term in Equation (2). In line with previous analyses, I assume that the treatment, affects inventive outcomes with a time lag (Kalemli-Özcan *et al.* 2010, 2013, Christensen *et al.* 2016). Taking the one year lag is an additional precautious way to consider the rigidity of inventive activities on a firm level. The empirical analysis assesses this specification as well as the lag structure in more detail.

5 Empirical results

5.1 Baseline results

As an initial step, Table 4 displays estimation results from the baseline specification from Equation (2) using patent filings as dependent variable.The coefficient of interest is positive and significant at the one percent level across several model specifications. This observation illustrates that relaxing financing constraints has a stimulating effect on patenting activities in quantitative terms. It verifies both previous empirical findings as well as the selected identification and estimation methodology. Results are robust to various definitions of the dependent variable (see Table A5 in Appendix D). Moreover, the effect is also economically significant: Moving the average firm from the pre- to post-integration period results in a 15 percent increase in patent filings for ex ante financially constrained firms.

- Insert Table 4 here -

[11] Following Bertrand *et al.* (2004), standard errors are heteroscedasticity-consistent and clustered at the firm level. In unreported regressions, estimations using alternative clusters, such as country- and country-industry levels, show that results are not sensitive to this particular specification.

As a next step and most central to the findings in this paper, I estimate a series of regressions using qualitative dimensions of firm-level patenting activities as dependent variables. First, I assess the impact of alleviating financial constraints on the technological quality of patented output. Columns I and II of Table 5 display negative and statistically significant correlation coefficients on the interaction of the FI_{ct} measure lagged by one period and forward citations, respectively claims. These results are in line with the presumption of a tradeoff between the quantity and quality of invented output. The exogenous easing of financing constraints induces firms to file patents of relatively lower average quality. The effects are of economic significance. For example, moving the average affected firm from the pre- to post integration period decreases patent quality (i.e. the patent claims measure) by about 33 percent.

Table 5 (Columns III and IV) contains results on the set of variables that relate to the market value of patents independent from the quality of the patents. Results suggest a weakly negative impact of changes in the availability of finance on the market value of patented inventions measured by the size of the patent family. Negative coefficients are significant at the five percent level. Specifications using renewals as dependent variable are statistically not different from zero.[12]

The relaxation of financing constraints triggers two contrasting effects, which potentially explains the lack of robustness in the estimates on market value. Relaxing financing constraints might have a negative effect on the market value, if constraints would work as a disciplining device. As such, it would be rational for a firm to file patents of lower quality as compared to its existing set of patents, once respective patents still deliver a positive net present value. Ceteris paribus, lower quality patents are expected to be active at fewer patent offices. At the same time however, firms might deploy available financial resources to extend their protection to a larger set of jurisdictions and not for filing new patents. Because I consider the number of jurisdictions at which a patent is active as a proxy of market value, this circumstance might on average balance out a potentially lower market value of patents. The same logic applies to patent renewals.

Table 5 (Column V) also displays regression estimates using the share of incremental and explorative patents among all patents filed by a firm as dependent variable. The interaction of financial integration and firms' share of incremental patents is positive and significant at the ten percent level. This suggests that those firms that benefit from relaxed financing constraints, on average, indeed introduce patents with a relatively lower impact and scope. Complementing this finding, estimates on the average number of patents protecting explorative inventions (Column VI) suggest that relaxed financing constraints lead to fewer explorative patents.[13]

- Insert Table 5 here -

5.2 Robustness tests and the lag structure

I. Variable specifications:

To ensure that the baseline findings are not driven by model specifications, I re-estimate the baseline regressions using various different specifications, sequentially introducing treatment and exposure variables. Results are not sensible to these adjustments and do not change much (see Tables A6-A8 in Appendix D). In addition, Table A9 in Appendix D displays baseline results using different

[12] Due to data specificities, renewals are only estimated for EPO patents and not those filed at national patent offices. This potentially biases results, i.e. explains the lack of statistical significance.

[13] It is important to regard these measures separately, because the categories define the outer ranges in a continuous space between incremental and explorative. For example, the negative effects on the share of explorative patents does not directly imply increases in incremental patents.

thresholds for determining whether firms are considered as treated or not. Estimates are similar to the original specification, but increase in size. Hence, using the median split as a categorization of exposed firms appears as a conservative approach.

Furthermore, using firm-specific average values of patenting measures might confound estimations. The distribution of success of inventive activities in terms of impact and value is oftentimes highly skewed. Because patenting measures in the baseline specification are based on the firm-specific, annual *average* of all patents filed, using maximum values in respective years potentially provides a different picture. For example, if a firm increases its patented output and thereby triggers a breakthrough invention, this might not be reflected in the firms' average patenting activities.

Based on these considerations, I repeat the baseline specifications using the firm-specific *maximum* of patenting measures on technological quality and market value as dependent variables. Positive coefficients of the interaction terms in these regressions would imply that firms are able to generate higher quality or more valuable patents despite lower average values. In contrast, estimates displayed in Table A10 (Appendix D) do not confirm this. While the effect on the maximum number of citations received and family size is still negative, estimates indicate no significant change for the number of maximum patent claims.

As a modification to the baseline specification, I deploy an alternative definition of explorative versus incremental patent. Because the two measures are constructed including several factors, one might argue that the particular variable specifications drive my results. To alleviate this concern, I use the so-called originality index, which is a simple and well-established measure in patenting literature (Trajtenberg *et al.* 1997, Hall *et al.* 2001). The index measures the technological range a patent relates to and describes the nature of research. Low scores of the originality index suggest a rather basic invention. The index should therefore mirror results related to explorative and incremental patents. I run regressions using two specifications of the originality index as dependent variable across several model specifications (Table A11 in Appendix D). Results are well in line with previous findings and support for notion of the agency theory of a negative effect of increased funding on the explorative dimension of patented inventions.

Next, I assess the appropriability of choosing the one year lag of the financial integration index, FI_{ct}, in the baseline specifications. Therefore, I repeat the baseline regression using different lag-levels as regressors. This exercise does not allow to make inferences on the exact timing of the effects, because the treatment variable is continuous. Instead, results displayed in Table A12 (Appendix D) show that using the first or second lag appears most appropriate. In most cases both the contemporaneous as well as the third lag of the FI_{ct} measure lack precision. Still, estimates generally increase in size using higher lag levels or remain at comparable levels between the first and third lag. Again, the findings point towards the validity of my empirical approach. At the same time, they illustrate that changes in the legislative framework require time to become measurable in terms of adjustments in real economic activities. Overall results of the tests in this subsection reassure my initial findings.[14]

II. Lag structure:

In the context of a quasi-natural experimental setup, it is necessary to address concerns regarding possible anticipatory effects (Bertrand and Mullainathan 2003). To investigate whether anticipatory effects exist, I test causality in the spirit of Granger (1969), which determines whether any pre-treatment trends are observable. The general idea is to analyze whether effects are measurable before causes and not vice versa. Because the initial implementation dates vary across countries,

[14] In unreported tests, I find that estimates are robust to country-specific weighting of the FI_{ct} measure with respect to the relative sizes of each country (i.e. by per capita GDP).

it is not feasible to display specific years but only years relative to the country-specific first year of FSAP Directives adoption. I therefore estimate regressions specified as in Equation (2) only that I exchange the interaction term $FI_{ct} \times Exp_i$ with the set of interactions $Year_{t-\tau} \times Exp_i$, with $\tau \in [1, 2, 3, 4]$. The reference year is the country-specific fourth year before the FI_{ct} measure departs from zero and the dataset is truncated to the pre-integration phase (i.e. $FI_{ct} = 0$). This setup suggests that coefficients of the interaction terms should not be different from zero, if both exposed and unaffected firms follow a common path. Across all patenting specifications, estimates in Table 6 are indeed consistent with this assumption. Note that due to perfect multicolinearity, Exposure $\times$ Year$_{t-4}$ coefficients are omitted. The remaining coefficients are not statistically different from zero at any conventional level of significance. Thus, the assumption of parallel pre-treatment trends among exposed and unaffected firms cannot be rejected.

- Insert Table 6 here -

The integration period itself is of particular importance in the context of this analysis. For instance, due to relatively high adjustment costs, it takes time for a firm to adjust their research activities in response to a shift in funding (Brown *et al.* 2009). Arguably, the staggered structure of the treatment variable partially accounts for this aspect by construction. Unlike a binary indicator that measures whether all relevant directives are implemented at a given time for all countries (i.e. in the year 2008), the continuous FI_{ct} variable reflects a cumulative process of multilateral adoption along the various amendments. However, as it seems plausible that adjustment processes in corporate research activities require some time to take effect, I investigate the timing of the effects in more detail. Similar to the analysis on anticipatory effects, I therefore assess the lagged response of relaxed financing constraints regarding firms' patented output by deploying interactions between the treatment indicator and country-specific year dummies. In this case, the year dummies represent the years relative to year $t = 0$ when the integration process was initiated in a respective country, i.e. $FI_{ct} > 0$.

Figure 4 displays results of this exercise for the technological quality and patent type variables separately. The graphs mirror baseline results regarding the sign of the relationship as well as the common pre-integration path at the onset of the FSAP. Because the treatment occurs continuously over the course of several years, it is intuitive that effects do not unfold during the first two years after implementation of the first directives. Similarly across specifications, coefficients turn significant only after three or four years which implies that integration takes about this much to become measurable in real economic terms.[15] In contrast, the lack of statistical significance in the results on market value are mirrored in the development of respective coefficients displayed in Figure A3 (Appendix E).

- Insert Figure 4 here -

5.3 Heterogeneity across firms

In order to better understand the relationship between relaxed financing constraints and patented inventions, I analyse heterogeneous treatment effects across relevant firm characteristics. Because, theoretical insight do not deliver a clear predict on the source of these effects a priori, investigating

[15] Table A13 (Appendix D) displays the corresponding average FI_{ct} values for the number of years relative to the country-specific initiation of the integration phase and shows that the measure takes the values of 0.428 and 0.643, for the third and fourth years after first implementation of FSAP Directive. This indicates that these are actually the years where more than 50 percent of the maximum value of the integration measure is surpassed.

these effects is essentially an empirical task. For example, financially constrained firms have to forgo some promising research projects (Hottenrott and Peters 2012), which induces rational firms to implement those projects of highest perceived value first. Alleviating these constraints causes firms to work also on relatively worse inventive projects among their possible set of alternatives as long as they have a positive net present value. This proposition of decreasing returns to investment can be directly applied in the context of R&D investments or patented inventions (Lokshin *et al.* 2008). From this perspective, it should be incumbent inventors, i.e. relatively active ex ante patenters, that drive results by enlarging their patenting activities on the intensive margin and therefore add less valuable patents to their portfolio.

An alternative explanation is that entry of previously rather inactive patenting firms causes patent quality to decrease. This consideration rests on the notion that increasing patenting costs effectively crowd out low-value, marginal patents (de Rassenfosse and Jaffe 2018). From a reversed angle, improved access to funding lowers (opportunity) costs to file patents. Hence, relaxed financing constraints potentially allow firms to file patents that are have zero or very little patenting activities before exhibiting a reduction in financing constraints. If this was the case, the role of funding as disciplining device in inducing more efficient allocation of available capital would apply.

- Insert Table 7 here -

To answer this ambiguity, I first estimate the total number of patents that each firm filed in the pre-treatment period (i.e. $FI_{ct} = 0$). Based on this, I categorized firms in the top quartile of the patenting distribution as frequent patentees and repeat the baseline regressions separately for each of the subgroups. According to results from in Table 7, effects are stronger for ex ante low patenting firms. Coefficients of this subgroup are much larger in relative size. Importantly, coefficients in the sample of ex ante frequently patenting firms are statistically not different from zero. This suggests that it is not the incumbents which start filing lower quality patents. Instead results suggest ex ante low patenting firms to add patents of lower average quality after exhibiting increase patenting activities due to better access to funding.

As a second step, I investigate whether certain industries are particularly prone to the effects. The high propensity to patent of this subset of firms is reflected, for example, in the sectoral distribution of sample firms as outlined in the data section. I therefore distinguish between the manufacturing sector and the remaining sectors and estimating separate regression respective subgroups (see Table A14, Appendix D). Results show that manufacturing firms account for the effect of mitigated financing constraints on patenting behavior.[16] This result appears plausible in the light of patentings' dominant role in tech-related sectors. Only if patenting is a potential business strategy, firms should be willing to file patents despite lower quality.

5.4 Financial integration and the use of bank loans

As an essential step to verify my empirical approach, I test whether there are indeed quantifiable effects of financial market harmonization on bank-firm relationships. If this was not the case, other effects must have driven results regarding firms patenting behavior. I therefore place a special emphasis on the analysis of the impact of FSAP on bank borrowing.

There are testable mechanisms through which financial market harmonization affects bank borrowing. Improvements in the legal setup typically entail more efficient allocation of capital.

[16] In unreported sets of regressions, I divided the manufacturing sector, for example, according to the OECD classification of high-tech sectors versus medium- and low-tech sectors. The coefficients of interest were virtually the same between high-, medium- or low-tech sectors.

The alignment of the legal framework resembles a removal of (formal) barriers, which pulls entry. Intuitively, market entry increases competition among banks. These changes in the competitive structure of domestic banks are accompanied by changing borrowing conditions (Chava *et al.* 2013, Amore *et al.* 2013, Cornaggia *et al.* 2015). As a consequence, financial market harmonization puts downward pressure on interest rates. Ceteris paribus, this increases demand for bank debt as it becomes relatively cheaper to obtain a loan. Moreover, financial integration changes the existing set of rules of all market participants reducing information asymmetries and risk. By definition, a relatively more integrated market entails a more similar set of rules as compared to a relatively less integrated market. This facilitates, for example, the use of collateral both for domestic and foreign firms. Hence, a reduction in information asymmetries and decreased collateral costs stimulates banks' propensity to supply loans (Liberti and Mian 2010).

These arguments suggest that financial integration reduces financing constraints by lowering interest rate spreads and thereby leads to increased use of external bank debt particularly for small firms (Cetorelli and Strahan 2006, Guiso *et al.* 2006). Hence, estimating whether the FSAP indeed has an effect on those two outcome variables is a plausibility test on the transmission of financial integration to firms' access to funding. I therefore repeat the previous exercises by assessing the effect of my integration measure (FI_{ct}) on both firms' borrowing activity as well as the interest burden.[17]

- Insert Table 8 here -

First, Table 8 shows estimates re-running baseline specifications from Equation (2) but using firms' bank loan-to-asset ratios as dependent variables. The impact of the financial integration measure is consistently positive and statistically significant at the one percent level across several specifications. This positive effect is robust to different model specifications, including several fixed-effects models as well as lagged dependent variables. Notably, the integration variable, FI_{ct}, is positive and statistically significant in the first two specifications (Columns I and II), whereas this effect disappears, once the interaction term is included (Column III). This suggests that the positive effect of integration is predominantly attributable to increases in bank loans for ex ante financially constrained firms. The coefficient of the interaction term in Column IV suggests an economically meaningful increase of the loan-ratio of 27 percent from pre- to post-FSAP implementation for an average ex ante financially constrained firms.

Next, estimations displayed in Table 9 display that financial integration relates negatively to the interest expenses during the period (Columns I and II). The coefficient on the FI_{ct} measure is negative and statistically significant. Including also the interaction of the exposure and treatment variable (Column III) shows that this negative effect is mostly driven by ex ante financially constrained firms. These firms face higher interest burden in the pre-treatment phase, as the positive coefficient on the exposure variable in Column III illustrates. This effect reverses over the course of the financial integration process, i.e. combined with the interaction term. The coefficient of interest is significant at the one percent level and economically meaningful. For a median firm facing an interest burden of 6.9 percent, the integration process means an effective reduction in the interest burden of about 30 percent, comparing pre- and post-integration levels.

- Insert Table 9 here -

[17] Because my data does not contain interest rates for individual loans, it is not possible to calculate the weighted average interest rates paid during the period. However, the data set contains information on the total amount of interest paid throughout the year, which allows estimating the interest burden by dividing total interest payments by the outstanding amount of loans.

To mitigate concerns that estimates are confounded by distinct model specifications, I apply alternative definitions of both the loan and the interest burden as dependent variable. Tables A15 and A16 (Appendix D) illustrate that these adjustments do not change results. Broader definitions on these variables result in lower values in the correlation coefficients. For instance, measuring the impact on total debt instead of bank debt (Table A15, Column IV) results in much lower estimates. Similarly, coefficient have the same sign but are of much weaker explanatory power when measuring interest burden by total financial expenses (Table A16, Column IV). These results speak in favor of the measures applied in the first place. In addition, I test the sensitivity of results regarding treatment variable specifications. Choosing different cutoff thresholds (i.e. Q50, Q33, Q25) that determine whether a firm is classified as financially constrained or not, does not change results qualitatively (Table A17 in Appendix D). In fact, when regarding relatively stronger constrained firms, effects become even more sizable.

Further, I analyze whether exposed and unaffected firms follow a parallel path in terms of their debt ratios and interest burden before the implementation of the FSAP. Analogue to respective tests on the baseline specification, I interact exposure dummies with country-specific year dummies relative to the first year where the FI_{ct} measure departs from zero. For an illustration of this, Figure 5 graphically summarizes the effects. The dependent variables for a repeated fixed-effect regression are i) the bank loan to asset ratio and ii) the interest burden of firms within the respective years. The coefficient plots show that the treatment induces a deviation from this common trend for affected firms. In the first two years prior to the country-specific onset of the integration, coefficients are not statistically significant from zero. This indicates that firms follow a common trend in the pre-treatment phase independent of whether they are affected by the legislative changes or not and confirms there are no anticipatory effects. Moreover, the plot illustrates the lagged impact of financial integration on the dependent variables. Coefficients deviate from the common trend after two to three years. Interest rate charges for affected firms decrease after the first implementation of the directives. At the same time, the use of bank loans increases in the treatment phase. Both effects are statistically significant and become stronger as integration evolves. This finding confirms that effects of FSAP are measurable and increase over the course of the implementation phase. The effect occurs delayed relative to the onset of the financial integration process, which favors the intuition of legal changes to require a certain time span to expand their full potential.

- Insert Figure **??** *here -*

The coefficient plots show that the treatment induces a deviation from this common trend for treated firms. In the first two years prior to the country-specific onset of the integration, coefficients are not statistically significant from zero. This indicates that treated and control firms follow a common trend in the pre-treatment phase and confirm the absence of anticipatory effects.

Moreover, the plot illustrates the lagged impact of financial integration on the dependent variables. Coefficients deviate from the common trend after two to three years. Interest rate charges for affected firms decrease after the first implementation of the directives. At the same time, the use of bank loans increases in the treatment phase. Both effects are statistically significant and become stronger as integration evolves. This finding confirms that effects of FSAP are measurable and increase over the course of the implementation phase. The effect occurs delayed relative to the onset of the financial integration process, which favors the intuition of legal changes to require a certain time span to expand their full potential.

Another way of testing the validity of the setup is to conduct a placebo analysis (Agrawal 2013). There may be unobservable forces that coincidentally affect ex ante constrained and unconstrained firms differently during the FSAP implementation phase. Placebo analyses rest on the logic of a falsification test. Hence, effects should only be observable where predicted by theory. I therefore artificially shift the integration measure five years forward. By this, I pretend that the financial market integration mainly occurred during the time of the introduction of the Euro as a common currency in Eurozone countries, resembling in a different period of financial integration in Europe (see Appendix C for more details). In line with my empirical strategy, I do not obtain comparable results regarding the enhancing effect of financial integration on firms' bank borrowing activities. As displayed in Table 10, the effect of financial integration on firms along all analyzed dimensions disappears in my placebo setup. The findings show that more financially constrained firms do not perform differently around the pseudo-event. Table A18 (Appendix D) confirms that this also applies when using qualitative patent dimensions as dependent variables.

- Insert Table 10 here -

Furthermore, observing average effects does not rule out that both measures move simultaneously but without a common cause. So far, the analyses make inferences on the *average* firm. Hence, I test whether those firms that experience better borrowing conditions during the integration period actually are also the firms that increase borrowing. Firms can be classified as beneficiaries from integration according to their average interest burden during the post integration phase, i.e. when $FI_{ct} > 0.66$ (compare with Table A12, Appendix D). Beneficiaries are those firms whose interest charges are lower in the post integration phase as compared to the average across the entire timeframe. This allows to repeat the baseline regressions from Equation (2) by using firms' bank loans as dependent variables in a triple interaction setup. More specifically, regressions include both the interaction term of treatment and exposure as well as the interaction term of treatment, exposure, and the beneficiary indicator. Estimates in Table A19 (Appendix D) reveal that firms which exhibit lower interest charges, indeed mostly account for the positive effect of the financial integration measure on loan ratios. While the coefficient of the triple interaction is positive and large, the coefficient of the interaction term is small in size and statistically not different from zero.

5.5 Instrumental variable approach: integration, funding, and patenting

All previous specifications use DID estimation techniques which requires that the identifying event is not implemented based on differences in outcomes (Bennedsen *et al.* 2007). In my setting, this implies that FSAP implementation is uncorrelated with firms' patenting behavior: a reasonable assumption given that my analysis focuses on one specific part in a series of supra-national legislative amendments that are quasi-randomly implemented in different points in time and across several member states. Even though it appears unlikely that FSAP Directives targeted individual firms' patenting activities many years in advanced, of course, endogeneity concerns can never be fully eliminated in an empirical assessment. For precautious reasons, I therefore describe the underlying logic of my empirical strategy in an alternative way. My identifying assumption presumes that financial integration affects firms' patenting activities *through* the bank loan channel. Conceptually, financial integration can thus be used as an instrument for firms' bank borrowing activities allowing the use of instrumental variable (IV) techniques in my setting.[18]

[18] Roberts and Whited (2012) find institutional amendments to be good instruments for IV estimations as long as the changes do not directly target the relationship under investigation. The main advantage of using IVs is a more explicit application of the sources of variation used to evaluate the impact of financial resources on inventive

The FSAP implementation is a valid instrument with regard to the necessary requirements as suggested by Angrist and Pischke (2008). First, the FSAP has to be as good as randomly assigned. As outlined in above, the implementation of FSAP amendments is a quasi-experimental setup that exogenously alleviates financing constraints. Similarly the ex ante determined exposure variable is also plausibly exogenous. Several preceding tests in the study at hand provide robust evidence on these assumptions. Second, the relevance condition requires that financial integration has explanatory power for bank debt. This is precisely what multiple tests in previous subsections demonstrate. Third, the exclusion restriction can be maintained. The decision to implement financial market amendments should not have a *direct* effect on the (quantity and) quality of firm-level patenting. In particular, none of the banking-related directives include direct or indirect measures regarding firm-level inventive output. As an empirical exercise on this consideration, the placebo test provides strong evidence that this criterion is satisfied.

The following system of equations summarizes the IV estimations:

$$\begin{aligned} \text{First stage:} \quad & Loans_{it-1} = \alpha_i + \alpha_{ct} + \alpha_1\, FI_{ct-1} + \alpha_2 X_{it-1} + \upsilon_{it}, \\ \text{Second stage:} \quad & Invention_{it} = \rho_i + \rho_1 \widehat{Loans}_{it-1} + \rho_2 X_{it-1} + \nu_{it} \quad , \end{aligned} \tag{3}$$

with $Loans_{it-1}$ measuring firm i's (logarithm of) total bank debt held at period $t-1$. Equations include a set of firm- and country-year-fixed effects and a vector of control variables which are specified as in the reduced form baseline setup in Equation (2).

- Insert Table 11 here -

Table 11 displays results from the IV regressions and finds that outcomes of the coefficient of interest are consistent with previous findings. First stage estimates document the positive and highly significant effect of the relevant FSAP amendments on borrowing. Further, regression coefficients on bank loans for the second stage estimations are positive and statistically significant when using patent filings as dependent variable. In contrast, coefficients are significant but negative when using quality dimensions as dependent variables. Across specifications, estimates confirm the baseline results suggesting a potential tradeoff between quantitative and qualitative dimensions of patented output. Importantly, previous findings prove to be robust regarding altering the setup towards a structural model by means of deploying an IV regression setup. Hence, this exercise eventually shows that my results are not driven by the specific econometric techniques applied.

6 Conclusion

In this study, I examine the impact of financial resources on firm-level inventive activities. Based on a unique and highly granular datasets my analysis finds that relaxing financing constraints induces firms to file more patent which are, however, on average of lower quality. To enable causal inferences, I use the staggered implementation of legal amendments in the course of financial market integration in the European Union throughout the 2000s as an identifying event. Deploying a DID estimation approach shows that moving the average affected firm from the pre- to post-integration period results in a 15 percent increase in patent filings. At the same time, affected firms file patents of lower technological quality, for example, resulting in a 33 percent decrease in quality

activities. This advantage comes at the costs that IV estimations should only be based on the subset of firms that is affected by the instrument (Angrist and Krueger 2001). When evaluating policy changes, however, DID remains a superior methodology if data on both pre- and post treatment phases for affected and unaffected entities are observed. For instance, policymakers are typically concerned about their actions' average effect on the total population.

when measured by patent claims. These results are economically significant and hold along several patenting dimensions. The results also suggest that affected firms change the actual types of patents filed. For instance, affected firms' patent applications cover fewer explorative inventions but instead tend to protect more incremental patents. To validate my results, I deloy a rich set of additional tests, such as analyses on anticipatory and parallel trends, different variable definitions and econometric specifications as well as several other plausibility tests, including placebo analyses.

Importantly, I show that these effects are heterogeneous across different firms. Most particularly, firms with a low propensity to file patents during the pre-treatment phase respond to relaxed financing constraints by filing more patents of lower quality and impact. This suggests that funding is a crucial imput for inventive activities and alleviating constraints helps firms to file more patents. For several firms this is accompanied with a relatively constant technological quality and market value. However, for firms with low ex ante patenting activities, financing constraints seem to work as a disciplining devise and can crowd out marginal inventors.

To reaffirm my empirical approach, I show that financial market integration increases affected firms' debt capacity by decreasing their interest rate charges. In turn, these firms intensify borrowing from banks. My results suggest that ex ante financially constrained firms were particularly affected by the exogenous shift in borrowing conditions induced by the FSAP. Moving the average firm from pre- to post-integration results in a 27 percent increase in bank loan to asset ratios over the course of about four years. Multiple tests point out that this relation is causal and thus provide evidence on the importance of public policies in supporting firm-level financing by improving borrowing conditions.

My findings primarily show that the impact of finance on inventive activities is more multilayered as commonly suggested. In fact, alleviating financing constraints does not only induce firms to file more patents but can also change which type of inventions are patented. My study therefore provides important insights on the limitations of managerial as well as governmental policies implemented to enhance research activities that exclusively rely on monetary aspects. Furthermore, my empirical setup assesses a recent political agenda aimed at strengthening integration in European markets. From a policy perspective, the results stress public policies' importance in supporting access to financial resources. At the same time, it is necessary to acknowledge that potentially beneficial decisions have diverse and possibly undesirable effects. The potential quantity-quality tradeoff highlights the importance of quality dimensions in evaluation the efficiency of research spendings.

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Tables from the main part:

Table 1: Definitions of patenting dimensions

Category	Name	Definition
Quantity	**1)** Patent filings	The sum of all patent applications within a year
Quality	**2)** Forward citations	The sum of all citations received within the first seven years after filing
	3) Claims	The sum of all claims made in the patent application
Value	**4)** Renewals	The number of annual renewal payments starting with the third year after filing
	5) Family size	The sum of EPC member states at which a patent was active in a given year
Patent types	**6)** Incremental patent	Both criteria have to be fulfilled: i) Not a high impact patent (a) ii) Not a high scope patent (b)
	7) Explorative patent	Both criteria have to be fulfilled: i) High impact patent (a) ii) High scope patent (b)
	a) High impact	Indicator = 1 if 3 out of 4 impact criteria are fulfilled, zero otherwise: i) Positive number of forward citations ii) > average forward-backward citation ratio iii) > average claims-backward citation ratio iv) > 80% A-type references
	b) High scope	Two relevant criteria fulfilled: i) > average patent scope ii) > average HHI concentration index on IPC classes

Notes: The table displays all patent-related variables, including their verbal definition. In the empirical analysis, all variables are normalized on an industry-year basis. Once firm i files more than one patent in period t, the unweighted average of the respective measures is calculated. 'Quality' refers to variables that signal both, quality and market value, whereas 'value' refers to variables only related to market value.

Table 2: Sample distribution across countries

Country	Observations	(in %)	Patents	(in %)
Belgium	7,044	(4.01)	32,811	(3.54)
Denmark	7,439	(4.24)	31,199	(3.37)
Finland	10,057	(5.73)	37,073	(4.00)
France	37,101	(21.15)	220,547	(23.82)
Germany	43,258	(24.65)	356,369	(38.49)
Ireland	2,242	(1.28)	7,122	(0.77)
Italy	1,069	(0.61)	1,798	(0.19)
Netherlands	10,352	(5.90)	52,704	(5.69)
Sweden	16,481	(9.39)	75,153	(8.12)
United Kingdom	40,414	(23.03)	111,249	(12.01)
Total	175,457	(100.00)	925,989	(100.00)

Notes: The table displays the distribution of observations in the main sample across different countries. Due to irregular coverage across the historical excerpts of the Amadeus database Austria, Greece, Portugal, and Spain are not included. Following previous studies (Kalemli-Özcan *et al.* 2013), I exclude Luxembourg, as its economy mainly consists of firms active in the financial industry. In addition the observation count, the table provides the absolute number of patents filed by firms located in respective countries. Parentheses next to respective values indicate the corresponding shares as fraction of total patents.

Table 3: Summary statistics, patenting and firm characteristics

Variable	Obs.	Mean	Std. dev.	Min.	Max.
Patent variables:					
1) Nr. of patents filed	175,457	5.152	40.358	0	2987
2) Forward cits. (7-yr.)	87,125	1.742	4.620	0	282
3) Claims	87,125	2.088	4.968	0	128
4) Family size	87,125	3.784	3.074	1	37
5) Renewals	87,125	0.469	1.322	0	18
Backward cits.	87,125	3.413	3.973	0	99
Patent scope	87,125	1.690	0.904	0	11
IPC concentration index	87,125	0.811	0.235	0	1
A-Type reference share	87,125	0.165	0.259	0	1
Originality-index (8)	87,125	0.325	0.282	0	0.984
Patent types (indicators):					
6) Incremental	87,125	0.433	0.200	0	1
7) Explorative	87,125	0.017	0.095	0	1
High scope	87,125	0.275	0.381	0	1
High impact	87,125	0.052	0.165	0	1
Firm characteristics:					
Debt-ratio	165,578	0.657	0.385	0	3.347
Bank loan-ratio	150,489	0.081	0.193	0	1
Interest burden	77,231	12.053	15.543	0	100
Age	173,990	29.2	25.420	1	125
Quoted	175,457	0.035	0.185	0	1

Notes: The table displays summary statistics on several measures of patenting activities. All variables are based on average firm-year observations. The definition on patent variables can be taken from Table 1. The financial variables are defined in Table A4 (Appendix D) respectively. In estimations, the variables are normalized by dividing the respective value by the industry-year specific maximum of this variable. Variables indicated with a number (1-7) resemble the set of dependent variables used to measure patent quality, values, and types in the baseline regressions.

Table 4: Baseline regression results: financial integration and patent filings

Dependent variable:	Patent filings			
	(I)	(II)	(III)	(IV)
FI	4.277	-0.900		
	(4.220)	(4.133)		
Exposure	3.760**	-0.770		
	(1.658)	(1.855)		
FI × Exposure		12.383***	11.635***	4.620**
		(3.960)	(3.625)	(2.283)
Debt-ratio	2.980*	3.117*	3.532**	1.772*
	(1.585)	(1.589)	(1.591)	(0.908)
Intangibles	0.775	1.796	2.049	-0.388
	(2.124)	(2.130)	(2.136)	(1.166)
Fixed assets	3.723	3.610	2.862	-0.062
	(3.683))	(3.674))	(3.657)	(1.544))
Age	-0.001	-0.001	-0.000	0.002
	(0.002)	(0.002)	(0.002)	(0.001)
Constant	9.783***	11.681***	9.380***	3.027***
	(2.635)	(2.415)	(2.510)	(1.423)
Additional controls:				
Macro-level	Yes	Yes	No	No
Industry-FE	Yes	Yes	No	No
Firm-FE	No	No	Yes	Yes
Country-Year-FE	No	No	Yes	Yes
Lagged dependent variable	No	No	No	Yes
Observations	33,858	33,858	33,858	33,858

Notes: This table presents estimates from panel regressions explaining the number of patent applications by a firm in a respective year. The main variable of interest is the DID estimator, i.e. the interaction of FI, and $Exposure$, as defined in Equation (2). To control for unobserved firm-, country-, industry, and time-specific heterogeneity, regressions include respective fixed effects, as indicated in the table. Macro controls, FI, and $Exposure$ variables are omitted in Columns III-IV, because of perfect collinearity arising from the inclusion of the fixed effects. Standard errors (in parentheses below coefficients) are heteroscedasticity-consistent and clustered at the firm level. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table 5: Baseline regression results: patent quality, value, and types

	Patent quality		Patent value		Patent types	
Dependent variables:	Forward Citations	Claims	Family size	Renewals	Incremental	Explorative
	(I)	(II)	(III)	(IV)	(V)	(VI)
FI × Exposure	-0.032***	-0.048***	-0.021**	-0.004	0.021*	-0.019**
	(0.011)	(0.011)	(0.010)	(0.009)	(0.011)	(0.009)
Debt-ratio	-0.009	-0.003	-0.003	0.002	0.008	-0.005
	(0.008)	(0.009)	(0.006)	(0.006)	(0.007)	(0.005)
Intangibles	0.018	0.004	-0.018	-0.024**	-0.014	-0.034***
	(0.013)	(0.014)	(0.011)	(0.011)	(0.013)	(0.012)
Fixed assets	0.013	-0.000	-0.023**	-0.004	0.019	-0.011
	(0.013)	(0.015)	(0.011)	(0.013)	(0.013)	(0.012)
Age	-0.001	-0.002**	-0.002**	0.000	-0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	0.136***	0.187***	0.356***	0.105**	0.450***	0.034
	(0.037)	(0.040)	(0.031)	(0.043)	(0.034)	(0.022)
Additional controls:						
Firm-FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year-FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	22,784	22,784	22,784	22,784	22,784	22,784

Notes: This table displays regression results from the baseline specification as defined in Equation (2). The dependent variables are previously specified patent quality (Columns I-II), value-related (Columns III-IV) dimensions, and different patent types (Columns V-VI). The main variable of interest is the DID estimator, i.e. the interaction of FI, and $Exposure$, as defined in Equation (2). Firm-specifc controls are defined in Table A4 (Appendix D). Estimates on fixed-effects are omitted but their usage is indicated in respective columns. Standard errors (in parentheses below coefficients) are heteroscedasticity-consistent and clustered at the firm level. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table 6: Lag structure: anticipatory effects

Category:		Patent quality		Patent value		Patent types	
Dependent variables:	Patent Filings	Forward cits.	Claims	Family size	Renewals	Incremental	Explorative
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
Exposure $\times$Year$_{t-3}$	-0.015	0.047	0.042	-0.021	-0.032	-0.012	-0.045
	(0.048)	(0.046)	(0.047)	(0.051)	(0.048)	(0.036)	(0.040)
Exposure $\times$Year$_{t-2}$	-0.000	0.053	0.071	-0.021	0.013	-0.012	-0.046
	(0.048)	(0.048)	(0.047)	(0.051)	(0.048)	(0.035)	(0.039)
Exposure $\times$Year$_{t-1}$	0.000	0.067	0.099**	-0.011	0.020	-0.033	-0.037
	(0.046)	(0.048)	(0.047)	(0.051)	(0.048)	(0.036)	(0.040)

Notes: This table presents estimates on the correlation coefficients of the interaction terms of the exposure variable with year dummies corresponding to the respective years before the integration process started, i.e. $FI_{ct} = 0$. The dataset is truncated to the pre-integration phase but the baseline regression specifications are maintained as defined in Equation (2). Only the interaction term $FI_{ct} \times Exposure_i$ is exchanged with $Year_{t-\tau} \times Exposure_i$, with $\tau \in [1-4]$. Hence, the reference year is the country-specific fourth year before integration started. All remaining variables and coefficients are not displayed but their use is indicated in the bottom of the table. The dependent variables include all relevant patent dimensions as defined above. Coefficients are obtained from different, repeated estimations using different lag levels as indicated in the first column. Standard errors (in parentheses) are heteroscedasticity-consistent and clustered at the firm level. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table 7: Heterogeneity across firms: frequent versus low patentees

Dependent variables:	Forward cits.	Family size	Incremental	Explorative
	(I)	(II)	(III)	(IV)
	Panel A: ex ante frequent patentees			
FI × Exposure	-0.024	-0.028	0.007	-0.007
	(0.020)	(0.019)	(0.017)	(0.018)
Controls:				
Firm-FE	Yes	Yes	Yes	Yes
Country-Year-FE	Yes	Yes	Yes	Yes
Observations	12,071	12,071	12,071	12,071
	Panel B: ex ante low patentees			
FI × Exposure	-0.040***	-0.024***	0.035***	-0.020*
	(0.011)	(0.009)	(0.015)	(0.011)
Controls:				
Firm-FE	Yes	Yes	Yes	Yes
Country-Year-FE	Yes	Yes	Yes	Yes
Observations	12,404	12,404	12,404	12,404

Notes: This table presents estimates on the coefficients of the interaction terms deployed as in previous regressions (e.g. Table 5). Results are retrieved from the baseline regression model as defined in Equation (2). The dependent variables include relevant patent dimensions defined in Table 1. Regressions are repeated on split samples according the categorization of being a frequent patentee (Panel A) or not (Panel B). Categorization is based on firms' ex ante filing activities: Firms with an above (below) average number of patents filed during the pre-treatement period are classified as frequent (low) patenters. The table displays the coefficient of interest of respective estimations. All remaining variables and coefficients are omitted. Standard errors (in parentheses) are heteroscedasticity-consistent and clustered at the firm level. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table 8: Panel regressions results: financial integration and bank borrowing

Dependent variable:	Log. bank loans			
	(I)	(II)	(III)	(IV)
FI × Exposure			0.214^{***}	0.270^{***}
			(0.046)	(0.072)
FI	0.172^{**}	0.164^{*}	0.062	
	(0.086)	(0.086)	0.089	
Exposure		-0.021^{***}	-0.028^{***}	
		(0.002)	(0.002)	
Debt-ratio	0.227^{***}	0.267^{***}	0.268^{***}	0.747^{***}
	(0.032)	(0.032)	(0.032)	(0.068)
Intangibles	-0.075^{**}	-0.038	-0.035	0.302^{***}
	(0.034)	(0.033)	(0.033)	(0.091)
Profitability	-0.144^{***}	-0.151^{***}	-0.152^{***}	-0.233^{***}
	(0.046)	(0.046)	(0.046)	(0.068)
Cash-Flow	-1.441^{***}	-1.370^{***}	-1.371^{***}	-1.054^{***}
	(0.055)	(0.055)	(0.055)	(0.102)
Age	0.015^{***}	0.007^{***}	0.007^{***}	0.025
	(0.001)	(0.001)	(0.001)	0.022
Constant	1.641^{***}	1.939^{***}	1.897^{***}	1.921^{***}
	(0.354)	(0.355)	(0.355)	(0.686)
Additional controls:				
Lagged dependent variable	Yes	Yes	Yes	Yes
Macro-level	Yes	Yes	Yes	No
Industry-FE	Yes	Yes	Yes	No
Country-FE	Yes	Yes	Yes	No
Firm-FE	No	No	No	Yes
Country-Year-FE	No	No	No	Yes
Observations	47,538	47,538	47,538	47,538

Notes: This table presents estimates from panel regressions explaining the logarithm of bank loans. The main variable of interest is the DID estimator, i.e. the interaction of FI_{ct} and $Exposure$, as defined in Equation (2); additional control variables are defined in Table A4 (Appendix D). To control for unobserved firm-, country-, industry, and time-specific heterogeneity, regressions include respective fixed effects, as indicated in the table. Macro controls, Coefficients on FI_{ct} and Exposure are omitted in Column IV, because of perfect collinearity arising from the inclusion of the fixed effects. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table 9: Panel regressions results: financial integration and interest burden

Dependent variable:	Interest burden			
	(I)	(II)	(III)	(IV)
FI × Exposure			-2.392***	-2.243***
			(0.538)	(0.772)
FI	-1.392*	-1.394*	-0.653	
	(0.767)	(0.767)	0.780	
Exposure		0.152	1.278***	
		(0.308)	(0.414)	
Debt-ratio	-1.405***	-1.423***	-1.460***	-4.387***
	(0.375)	(0.379)	(0.379)	(0.858)
Intangibles	0.454	0.435	0.389	0.118
	(0.439)	(0.439)	(0.438)	(1.050)
Profitability	1.862***	1.864***	1.842***	2.405***
	(0.673)	(0.673)	(0.672)	(0.995)
Cash-flow	2.098**	2.067**	2.085**	3.028*
	(0.872)	(0.875)	(0.875)	(1.552)
Age	0.010***	0.013*	0.013*	-0.013
	(0.006)	(0.007)	(0.008)	0.048
Constant	22.705***	22.599***	22.532***	15.881***
	(3.089)	(3.088)	(3.088)	(1.791)
Additional controls:				
Lagged dependent variable	Yes	Yes	Yes	Yes
Macro-level	Yes	Yes	Yes	No
Industry-FE	Yes	Yes	Yes	No
Country-FE	Yes	Yes	Yes	No
Firm-FE	No	No	No	Yes
Country-Year-FE	No	No	No	Yes
Observations	22,652	22,652	22,652	22,652

Notes: This table presents estimates from panel regressions explaining firm-level interest burden on external debt. The main variable of interest is the DID estimator, i.e. the interaction of FI_{ct} and $Exposure$, as defined in Equation (2); additional control variables are defined in Table A4 (Appendix D). To control for unobserved firm-, country-, industry, and time-specific heterogeneity, regressions include respective fixed effects, as indicated in the table. Macro controls, coefficients on FI_{ct} and Exposure are omitted in Columns III-IV, because of perfect collinearity arising from the inclusion of the fixed effects. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table 10: Placebo regressions: patenting, bank borrowing, and its costs

Event:	FSAP			Placebo		
Dependent variables:	Bank loans	Interest burden	Patent filings	Bank loans	Interest burden	Patent filings
	(I)	(II)	(III)	(IV)	(V)	(VI)
FI × Exposure	0.270***	-2.243***	4.620**	0.170	0.050	0.008
	(0.072)	(0.772)	(2.283)	(0.128)	(1.574)	(0.067)
Additional controls:						
Firm-level	Yes	Yes	Yes	Yes	Yes	Yes
Firm-FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year-FE	Yes	Yes	Yes	Yes	Yes	Yes
Lagged dep. variable	Yes	Yes	Yes	Yes	Yes	Yes
Observations	47,538	27,652	33,858	25,897	16,081	12,444

Notes: This table presents estimates from panel regressions explaining the logarithm of bank debt, the main specification of interest burden (interest expenses over average debt during the period) as well as the logarithm of patent filed per year (excluding zeros). Columns I - III display results during the sample period (2000-2008) when the actual implementation of FSAP took place. Columns IV - VI display results during the placebo-event (1997-2004) as in Appendix C. The main variable of interest is the DID-estimator, i.e. the interaction of FI and Exposure, which are defined in the baseline setup from Equation (2). Regression specifications are restrictive by including firm- and country-year fixed effects as well as the lagged dependent variable. Respective coefficients are omitted but their use is indicated in the columns. Standard errors (in parentheses below coefficients) are heteroscedasticity-consistent and clustered at the firm level. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

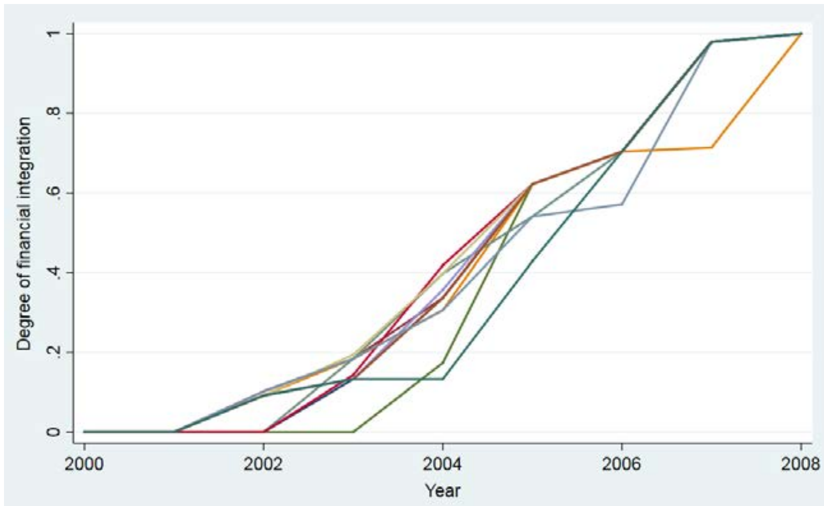
Table 11: IV regressions: financial integration and patenting activities

Category:		Patent quality		Patent value		Patent types	
Dep. variables:	Patent Filings	Forward cits.	Claims	Family size	Renewals	Incre-mental	Explora-tive
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
	Second stage: Dependent variable is patenting outcome						
Bank loans (log.)	0.101***	-0.131***	-0.285***	-0.180***	-0.149***	0.015*	-0.006
	(0.024)	(0.035)	(0.051)	(0.027)	(0.021)	(0.009)	(0.005)
Intangibles	-0.020	0.021	0.036	0.009	-0.016	-0.008	-0.010
	(0.013)	(0.073)	(0.110)	(0.057)	(0.016)	(0.019)	(0.011)
Fixed assets	-0.047**	0.171*	0.276**	0.195***	0.072	0.020	-0.027*
	(0.019)	(0.094)	(0.138)	(0.067)	(0.056)	(0.021)	(0.015)
Age	0.002	0.842***	1.041***	0.526***	0.566***	-0.176***	0.025
	(0.006)	(0.132)	(0.187)	(0.101)	(0.076)	(0.032)	(0.017)
	First stage: Dependent variable is bank loans (log.)						
FI	1.884***	3.748***	3.748***	3.748***	3.748***	3.748***	3.748***
	(0.684)	(1.208)	(1.208)	(1.208)	(1.208)	(1.208)	(1.208)
Additional controls:							
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year-FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-statistic	15.43	8.84	6.78	6.56	11.03	7.08	1.02
Observations	58,744	5,481	5,481	5,481	5,481	5,481	5,481

Notes: This table presents the main coefficients of IV regressions estimating on the effect of changes in bank loans on patenting. The endogenous variable instrumented in the first stage is the financial integration measure as defined in Equation (1). The estimation is specified in Equation (3). The dependent variables include all relevant patent dimensions as defined above. Firm-specific controls are defined as in Table A4 (Appendix D). Estimates on fixed-effects are omitted but their usage is indicated in respective columns. Regressions are estimated based on a sample of ex ante financially constrained firms. Results on the first stage are indicated in the bottom of the table and report the main variable of interest. First-stage F-statistics are robust Kleibergen-Paap Wald F-statistics. Standard errors (in parentheses below coefficients) are heteroscedasticity-consistent and clustered at the firm level. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

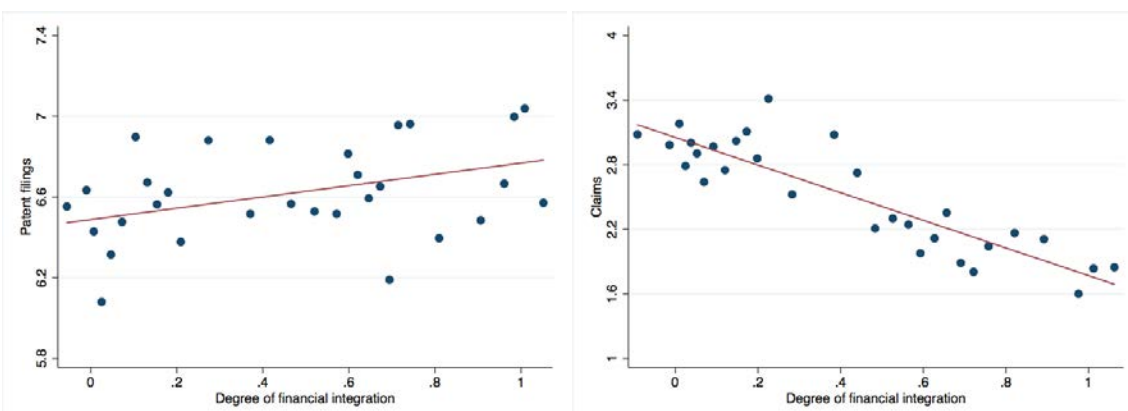
Figures from the main part:

Figure 1: Treatment variable: FSAP integration measure (2000-2008)



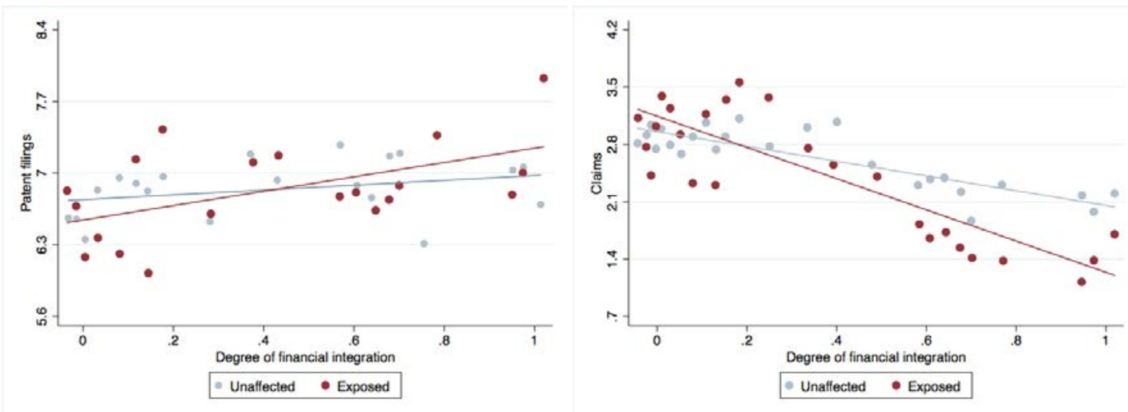
Notes: The table plots the different evolvements of the integration variable, FI_{ct} as defined in Equation (1) on the y-axis over the sample timeframe. Each color represents one of the sample countries. Values of this continuous treatment variable range between 0 and 1, indicating low (= 0) and high (= 1) multilateral implementation of respective directives.

Figure 2: FSAP measure and patenting: quantity versus quality



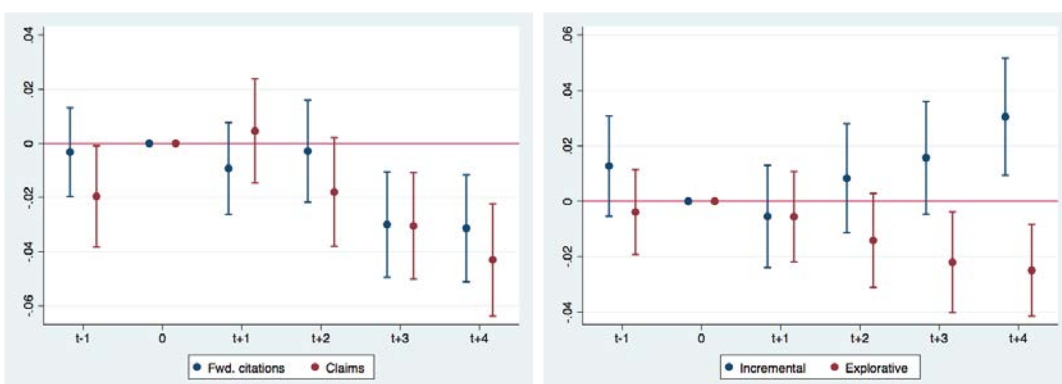
Notes: These binned scatterplots illustrate the relationship between the FI_{ct} measure as defined in Equation (1) and patenting activities, which are plotted on the x- and y-axis, respectively. In the left plot, patenting refers to the number of patents filed per firm and year. In the right plot, patenting refers to the average number of claims of a firm among all patents filed within the respective year. The number of bins is 30.

Figure 3: Patenting, integration and ex ante constrained firms: quantity versus quality



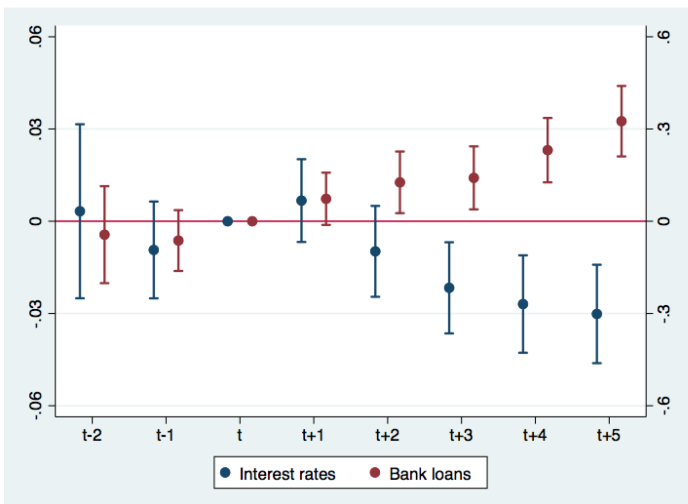
Notes: These binned scatterplots illustrate the relationship between the FI_{ct} measure as defined in Equation (1) and patenting activities, which are plotted on the x- and y-axis, respectively. In the left plot, patenting refers to the number of patents filed per firm and year. In the right plot, patenting refers to the average number of claims of a firm among all patents filed within a year. The sample is split according to ex ante constrained (red) and unconstrained firms (gray), i.e. firms exposed to and unaffected by the treatment. The number of bins for each group is 25.

Figure 4: Coefficient plot: the lagged impact of financial integration on patent quality and patent types



Notes: This figure plots the regression coefficients of the interaction terms of the exposure variable with a set of time dummies. The time dummies are country-specific indicators on the years before and after $(t+\tau)$ the FI_{ct} measure as defined in Equation (1) deviates from its initial value of zero (with $\tau \in [-1, 4]$). The regression is specified by: $Dep.\,variable_{it} = \eta_i + \gamma_{nj} + \alpha_1 Exp_i \times year_{t+\tau} + \alpha_2 X_{it} + \epsilon_{it}$, where the dependent variables are normalized values of forward citations and claims (left graph) as well as patent type classifications incremental or explorative (right graph), respectively. Whiskers represent 5 percent confidence intervals.

Figure 5: Coefficient plot: the impact of financial integration on bank borrowing and its costs



Notes: This table plots the regression coefficients of the interaction terms of the exposure variable with a set of time dummies. The time dummies are country-specific indicators on the years before and after $(t+\tau)$ the FI_{ct} measure as defined in Equation (1) deviates from its initial value of zero (with $\tau \in [-2, 5]$). The regression is specified by: $Dep.\, variable_{it} = \eta_i + \gamma_{ct} + \alpha_1 Exp_i \times year_{t+\tau} + \alpha_2 X_{it} + \epsilon_{it}$, where the dependent variable is either the logarithm of bank loans (indexed on the right hand side) or interest rates. Interest rates (indexed on the left hand side) are approximated by interest expenses over debt in the current year. Whiskers represent 95 percent confidence intervals.

Appendix A:

Defining and measuring relevant patenting dimensions

Differentiating among patent quality and patent value is challenging. Ceteris paribus, a patent of higher technological quality should deliver higher value for the patentee. The reverse is not necessarily true, as some factors affect market value despite being unrelated to the quality of a patent. For instance, the size and regulatory framework of the respective market the patentee is located in affects the potential to extract value from a given invention (Aghion *et al.* 2015). However, these aspects are not directly related to the patent quality. In line with de Rassenfosse and Jaffe (2018), in my empirical setup I differentiate among factors that are both quality and value relevant as well as those that are only considered to be value relevant. I therefore try to isolate purely value-relevant aspects from those that also relate to technological quality.

i) Measuring patent quality:

A well-known dimension of patent quality is forward citations. They refer to the number of citations a particular patent receives after it has been granted. Forward citation counts from the EPO also take into account patent equivalents, i.e. patent documents that protect the same invention at several patent offices (Webb *et al.* 2005). To assure comparability, I consider only the citations made within the first seven years after the publication date. This seems plausible, as the average time span between filing and publication is 18 months (Squicciarini *et al.* 2013). The number of forward citations mirrors the technological importance of a patent for subsequent technologies and serves to indicate the economic value of inventions (Harhoff *et al.* 2003). A higher citation count therefore indicates higher patent quality in technological terms.

Yet, measuring patent quality exclusively by means of citations can be an issue, because their distribution is strongly skewed, i.e. most patents receive zero or very few citations (de Rassenfosse and Jaffe 2017). I therefore additionally consider patent claims to be a relevant indicator for the quality of a patent. According to the European Patent Convention (EPC 1973), patent claims "*define the matter for which protection is sought*" (Art. 84), whereby at least one or more claims are required for an eligible patent application at the EPO. I consider the absolute number of claims enclosed in a patent application. Literature shows that this number reflects the patent's technological breadth as they determine the boundaries of the exclusive rights of a patent owner as only the technology or aspects, which are covered in claims, can be legally protected and enforced (Zuniga *et al.* 2009).

ii) Value-related measures:

Literature points out that there are distinct measures related to the value of a patent. For example both, the number of patent offices a patent is filed at as well as the frequency of patent renewals, signal its underlying value despite being relatively independent from its quality (Schankerman and Pakes 1986, Harhoff *et al.* 2003, de Rassenfosse and Jaffe 2018).

The first value measure considers the number of different patent offices at which a patent was filed, i.e. the so-called family size of a patent. According to the Paris Convention for the Protection of Industrial Property from 1883, inventors can apply for protection in any contracting states, once their patent application was approved (WIPO 2017). Protection in multiple countries is costly, because additional fees have to be covered at each patent office. Hence, willingness to incur these costs might resemble a higher underlying patent value. Indeed, several authors found the geographical scope of patents to be associated with patent value (Lanjouw *et al.* 1998, Harhoff *et al.* 2003, Squicciarini *et al.* 2013). I estimate the family size of a patent by counting the absolute number of patent offices at which the patent was filed throughout its lifetime. For a subsample, I can exploit the fact that each patent can be lapsed in each jurisdiction independently by generating a dynamic count of the family size.

Second, in order to perpetuate the protection by a patent, firms have the opportunity to pay an annual fee for a maximum of 20 years after initial approval. According to the European Patent Convention (EPC 1973, Art. 86), the fee is due beginning with the third year of protection and subsequently each year. The respective amount increases over the duration of protection. Even though firms also have to pay for the application of a patent itself, the sum of renewal fees exceed those costs by far (see Figure A4 below). Further, if the fee is not paid within the first six months of the due date, the patent is automatically withdrawn and protection terminates. The EPO documents post-grant events in their database, i.e. payment of renewal fees or lapse of patents. Because of the repeated decision of incurring the costs of annual renewal, only valuable innovations will be renewed multiple times (Schankerman and Pakes 1986).

According to EPO (2018) renewal fee payments are a direct indicator for the validity of a patent. In addition to a simple count, I construct a variable ranging from 0 to 1, which indicates how many years a patent renewal fee was paid as a fraction of the possible maximum protection length.

- Insert Figure A4 here -

Notable in the context of this study is that both factors can be directly related to patenting costs. With each year and each jurisdiction the costs of patenting increase. Figure A4 displays the cumulative costs of patenting given the fee EPO's structure in 2008, i.e. at the end of my sample period. The graph stylizes that application costs, including examination and granting fee, constitute about one tenth of the cumulative costs of renewals. Further, due to the specific fee structure with increasing number of patents and family size, patenting costs increase exponentially during the first 10 years and afterwards linearly.

iii) Invention types:

Regarding the overall direction of an invention, literature commonly differentiates among explorative and incremental (also referred to as exploitative) inventions (e.g. Henderson 1993, Chava *et al.* 2013). Differentiating among these categories remains important as it signals the potential to influence future progress. Both types of innovative activities are valuable as they fulfill specific targets. While exploitative innovations are based on successive, minor improvements, explorative innovations involve experimentation with potentially groundbreaking outcomes (Henderson 1993). In my analysis, I consider patent types as being explorative, i.e. having a broad scope and high impact, or incremental. Identifying different patent types cannot be achieved by considering single approximations for each category. Thus, I establish several types of patented inventions by defining multiple criteria, specifying a patent to classify for the respective type.

a) Explorative: Broad scope and high impact patents

Scholars have highlighted the importance of key technologies in driving economic change and growth. In their seminal paper, Bresnahan and Trajtenberg (1995) characterize so-called general purpose technologies by having the potential for pervasive use in several segments of business at the same time. Their great advantage is that they foster generalized productivity gains by spreading throughout the economy and triggering spillovers.

Several aspects are required for an invention to be considered as general purpose technology (Bresnahan and Trajtenberg 1995, Rosenberg and Trajtenberg 2004). It should i) exhibit general applicability relevant for the functioning of a broad set of products or processes, ii) have the potential for sustained optimization, and iii) feature a high degree of complementarity, particularly in downstream sectors. The combination of these features suggests a long-lasting impact on productivity and output.

For identifying the degree of generality of a patent, my measurement strategy is closely related to the approach as initially proposed by Trajtenberg *et al.* (1997). Their generality index utilizes information on the distribution of forward citations and International Patent Classification (IPC) classes contained in the citing patent documents. I consider not only the scope, or degree of diversity, regarding technology classes as relevant but additionally take into account the degree of the ex post market impact.

Specifically, for these two dimensions (scope and impact) I define several variables as relevant proxies. The scope of a patent can be defined following Lerner (1994) by deriving distinct 4-digit IPC subclasses to which an invention is categorized to. To take different weights in the distribution across IPC classes into account, I do not only regard their absolute number but also consider a concentration index, i.e. Herfindahl index of technology classes.[19].

Further, I use four criteria that qualify a patent as a high impact patent. First, I consider the share of claims as a fraction of backward citations. Relevant patents, which were previously filed and became relevant for new patents, should be listed in the patent application document. These references are so-called backward citations. Hence, if the number of new claims relative to the number of backward citations is high, a patent can be considered as rather novel. Second, a patent needs to have at least one citation (excluding self-citations) received. Otherwise, one cannot reliably claim that a patent was considered as relevant. Third, to further specify the impact of a patent the number of citations received as to be higher than the annual average of all citations received by patents in the same industry. Finally, I also consider the share of A-type references. References included in a patent are classified according to their relevance.[20] Category A applies only if a reference is not prejudicial to the novelty or inventive step of the claimed invention. I assume that high impact patents should include a high share of these type of references. Hence, I consider a threshold of 80 percent as a relevant criterion. Overall, three out of these four criteria need to be fulfilled in order for me to classify a patent as having a high impact. Hence, an explorative patent can be expected to exhibit both a high impact and scope.

b) Incremental patents

In line with literature, exploitative innovations are of more incremental nature and bear only relatively low risk. Notably, these types of inventions are of high importance, too. Progress, in general, and inventions, in specific, can be considered as a cumulative process (Raiteri 2018), and therefore strongly depends on small and steady improvements. As such, incremental inventions enhance the efficiency of existing technologies by improving inventions step-by-step (Ahuja 2000).

To quantify whether a patent can be considered as incremental, I consider four proxies to be relevant. First, the patent should be classified only in one specific IPC4 category. This resembles a limited scope, which is in line with the exploitation strategy behind incremental inventions.

[19]The measure ranges between 0 and 1, indicating low (0) and high (1) concentration of IPC classes, respectively. A Herfindahl index equal to one resembles a patent, which relates to only one distinct IPC class. The lower the index, the more IPC classes are relevant.

[20]The most common classifications are X-, Y-, and A-type references. Category X applies whenever a reference taken just by itself would not support that the claimed invention could be considered to involve an inventive step. Similarly, category Y applies, if a document, which is combined with at least one other document, is such that a claimed invention cannot be considered as an inventive step.

Second, relative to other inventions, an incremental invention should have fewer claims. Because claims reflect the technological breadth of the underlying invention, a relatively low level of claims symbolizes more narrow boundaries and, hence, a more incremental inventive step (Zuniga *et al.* 2009). I consider a patent to have relatively few claims, if its claims-to-backward-citation ratio is below the industry-year specific average. Third, similar to the argument above, I also consider the share of A-type references in this context. With a sufficiently low share, i.e. 20 percent, a patent contains mainly references that cannot support the presence of an inventive step. Finally, incremental inventions should not receive as much attention as more radical ones. My last proxy is therefore whether a patent has received zero citations within the first five years after filing. As with the criteria on explorative inventions and in order to allow flexibility in the measure, three out of these four criteria should be fulfilled to regard a patent as incremental.

Appendix B:

On the empirical mechanism and endogeneity concerns

Out-of-sample evidence on financial integration:
In order for my empirical approach to be valid, the legislative changes have to entail *de facto* changes. Hence, financial integration has to be imperfect prior to the introduction of the FSAP, while ex post it should have quantifiable improved as a result of the changes in EU law.[21] Assessments on the situation before the FSAP introduction provide evidence for a notable fragmentation of European markets. For example, Adjaouté and Danthine (2003) find that consumption growth rates in the Euro Area were less correlated than GDP growth rates suggesting that risk-sharing opportunities were not exploited. This is a distinct measure of integration and complements a study by Adam *et al.* (2002), who show that consumption in member states was not affected by idiosyncratic changes in GDP growth rates of other member states in the pre-FSAP period.

In addition to a lack of integration during the late 1990s, evidence points towards a strong increase thereof as a result of the FSAP. Kalemli-Özcan *et al.* (2013) show that business cycle synchronization was strongly enhanced as a direct effect of the FSAP. In a more general manner, Meier (2019) and Malcolm *et al.* (2009) further stress the importance of the amendments for providing confidence in the reliability of financial regulation itself. Likewise, Quaglia (2010) argues that the FSAP represented a change in EU strategy away from market opening measures and towards common regulatory measures.[22] Aggregate statistics support this idea. Figure A5 plots quantity- and price-based indicators of financial integration as defined by the European Central Bank. Both indices document a rapid integration phase during the mid-2000s. Combining all these aspects confirms that the implementation process of the FSAP Directives notably increased financial market integration within Europe.

- Insert Figure A5 here -

Empirical mechanism:
Two distinct mechanisms account for measurable improvements in borrowing conditions caused by legal amendments regarding financial harmonization. First, cross border lending is enhanced due to facilitated movement of capital. Fragmented markets that are based on differences in legal requirements across individual EU member states entail increased risk and information asymmetries which constitute an important impediment for foreign investment (Haliassos and Michaelides 2003). By definition, a relatively more integrated market entails a more similar set of rules as compared to a relatively less integrated market. Aligned regulatory requirements induce reliability and transparency for potential credit suppliers. At the same time it lowers investors' costs of acquiring relevant information (Huberman 2001). If these cost improvements are passed through to borrowers, demand for loans increases eventually alleviating restricted access to financial resources.

[21] In a financially integrated market all market participants with the same characteristics i) face a single set of rules, ii) have equal access to financial instruments, and iii) are treated equally when they are active in the market (European Central Bank 2016). Hence, both investors and borrowers interact on a level playing field which, however, does not imply the reduction of market frictions per se. Instead, financial integration is concerned with the (a)symmetric effects of existing frictions on different areas. The elimination of market failures are not a prerequisite for defining a financial market as being fully integrated as long as frictions are symmetric across all regions. Financial structures, habits, and their interrelation established prior to the integration may persist even after legal harmonization.

[22] These observations do not imply a full achievement of integration as a result of the legislative amendments. Still, given the level of integration of European markets was relatively lower before the introduction of the EU's integration plans, cross border legislative agreements certainly contributed to enhance integration in relative terms.

For example, Haselmann *et al.* (2009) provide evidence that access to bank loans improves for firms domiciled in previously less integrated markets, resulting in increased borrowing activity.

Second, financial integration changes the existing set of rules of all market participants and therefore also affects domestic banking activities. Improvements in the legal setup allow a more efficient allocation of capital by reducing frictions in the financial intermediation process which stimulates domestic lending conditions. For instance, Liberti and Mian (2010) argue that decreased collateral costs mitigate borrowing constraints. In addition, market entry of firms resembles an increase in competition due to the removal of (formal) barriers. Literature shows that changes in the competitive structure of domestic banks are accompanied by changing lending conditions (Chava *et al.* 2013, Amore *et al.* 2013, Cornaggia *et al.* 2015).

Importantly, empirical evidence points out that these two mechanisms indeed apply. Malcolm *et al.* (2009) finds that the FSAP amendments facilitated the use of as well as the procedures of obtaining financial collateral in the European financial market. Moreover, one distinct example of the FSAP directives is the implementation of the Basel II Accords, as of June 2004 via the so-called Capital Requirements Directives. For a given level of risk, it allows banks to reduce their regulatory capital requirements for claims on SMEs, which are specifically important regarding my data. The directives therefore directly improve small firms' access to bank funding (Aubier 2007).

Mitigating endogeneity concerns:

The specific modeling of the measure allows me to mitigate endogeneity concerns for several reasons. First, I argue why the elements of the FSAP in the integration measure, namely EU Directives, can be considered as non-anticipatory. Aside of 28 Directives, the 42 amendments stipulated by the FSAP also encompassed several regulations, recommendations and comments. These other instruments potentially work against my empirical strategy, because they do not result in changes in law (recommendations and comments) or they are strictly binding at a pre-defined and therefore potentially anticipated point in time (regulations). In contrast, EU Directives become effective on an individual country-specific basis after passing domestic legislation. This transposition process is notoriously slow, as it demands for modifications of existing institutional structures, the removal of previous regulations, and oftentimes the renewal of agencies and infrastructure. In practice the implementation of EU Directives usually requires multiple years and varies considerably across member states (Kalemli-Özcan *et al.* 2010, 2013). I take advantage of this circumstance by measuring integration not only as a simple count of implemented directives in a respective country at a certain time, but instead weighting this implementation by the number of other EU members that have also implemented the same directive. Hence, my integration measure will capture the multi-lateral nature of legal harmonization processes on supra-national levels. Moreover, I only regard seven directives related to the banking sector. This is plausible, because I therefore focus on legal changes that have a direct impact on the variable of interest, i.e. external bank finance.

Second, the sequential implementation of the FSAP Directives is unlikely to pick up market responses. The general implementation schedule was set years in advanced by the European Commission. While the transposition windows for implementing each directive is quite narrow, variations in domestic implementations are occur due to differences in aforementioned national legislative procedures. Furthermore, the implementation of the directives is unilateral (at domestic level), whereas financial integration is a multilateral concept (Kalemli-Özcan *et al.* 2013). Hence, the FSAP Directives resemble political decisions made years in advanced, so that implementation is unlikely to reflect market responses several years later (Christensen *et al.* 2016).

Third, individual firms' actions might be related to specific country initiatives. This could be problematic, as estimations are made on the firm level. However, in my setup implementation decisions are made on a supra-national, European level, which mitigates this concern (Schnabel and Seckinger 2019).

Combining the above suggests that in order for endogeneity to be of a concern, countries would have to experience differentially timed local shocks, each promoting lawmakers to start transposition. These actions would have to be anticipatory in nature and reflect firm-specific issues, which are additionally only relevant for specific firms. Eventually, it appears unlikely that FSAP directives targeted medium termed innovative activities many years in advanced.

Appendix C:

Placebo test - impact of financial integration on bank loans

In the main part, I provide evidence on the enhancing effects of the implementation of FSAP directives regarding firm-level bank borrowing. One way to further test the validity of this effect is to conduct a placebo analysis. I simulate the FSAP by shifting the values for the integration measure five years forward. Hence, I pretend that the main part of financial market integration (which occurred by 2004) of the FSAP happens during the year of the introduction of the Euro as a common currency in Eurozone countries. If it was generally the case that major changes in financial integration function as a positive shock on borrowing, I would expect to find similar results for this event, too.

Presumably, the introduction of the Euro should not have similar effects as the FSAP on borrowing condition, despite the fact that it can be considered as one of the major elements of financial integration in the EU in the years preceding the FSAP. The common currency affects investment behavior by eliminating or at least significantly lowering exchange rate risk and other transaction costs, which usually hamper foreign investments.[23] In their empirical analysis, Haselmann and Herwartz (2010) observe that the harmonization of the currency regime leads to an increase in intra-Eurozone investment. Still, the authors stress that important factors accountable for distorting investment prevail even after the introduction of the Euro. While the single currency eliminates exchange rate risks and reduced transaction costs, information asymmetries are not notably influenced by the unification of the European currencies. Therefore, financial integration initiatives prior to the FSAP does not effectively mitigate informational asymmetries and, in turn, financial constraints of respective European firms.

In order to both test this presumption and to validate my empirical strategy further, I run a placebo test. Integration takes effectively place once the majority of involved parties implement a certain set of rules. Consequently, the timing of the placebo integration resembles that the majority of integration took place in 2000, the year after the Euro introduction. As displayed in Table A17 and A18, the positive effect of financial integration as well as the enhancing effect of integration captured by the interaction term of treated times treatment, disappears in my placebo analysis. When replicating the regression of treatment and exposure on firm-level bank debt ratios, I find no statistically significant results for the pseudo-event. This further strengthens the assumption that I measure a true causal effect.

[23] For instance, prior to the Euro introduction a representative investor has the choice between investing i) domestically, ii) within the Eurozone, or iii) outside the Eurozone. Her decision ultimately depends on the respective expected returns, her degree of risk aversion as well as the (co-) variances of the returns (Haselmann and Herwartz 2010). The former two aspects should remain unaffected after the introduction of a single currency. However, the variance of intra-Euro zone investment returns decreases, because exchange rate movements are cleared out entirely. Similarly, some transaction costs are eliminated for investments within the Eurozone.

Appendix D: Tables (A1-A19)

Table A1: Sample distribution across sectors (NACE Rev. 2)

Category	**Obs.**	**(in %)**	**Patents**	**(in %)**
A - Agriculture, forestry, and fishing	924	(0.53)	1,451	(0.16)
B - Mining and quarrying	738	(0.42)	11,351	(1.22)
C - Manufacturing	88,275	(50.31)	566,435	(61.17)
10 - Food products	2,240	(2.54)	7,518	(1.33)
11 - Beverages	271	(0.31)	597	(0.11)
12 - Tobacco products	67	(0.08)	428	(0.08)
13 - Textiles	1,658	(1.88)	3,172	(0.56)
14 - Wearing apparel	545	(0.62)	699	(0.12)
15 - Leather and related products	319	(0.44)	505	(0.09)
16 - Wood products, excluding furniture	1,441	(1.63)	1,963	(0.35)
17 - Paper and paper products	1,723	(1.95)	7,873	(1.39)
18 - Printing and reprod. of recorded media	959	(1.09)	1,283	(0.27)
19 - Coke and petroleum	172	(0.19)	1,239	(0.22)
20 - Chemicals and chemical products	5,196	(5.89)	71,751	(12.67)
21 - Pharmaceuticals	2,570	(2.91)	41,948	(7.41)
22 - Rubber and plastics	7,003	(7.93)	30,798	(5.44)
23 - Other non-metallic mineral products	2,967	(3.36)	11,278	(1.99)
24 - Basic metals	1,643	(1.86)	9,015	(1.59)
25 - Fabricated metals	11,842	(13.41)	35,823	(6.32)
26 - Computer, electronics, optical products	9,940	(11.26)	59,014	(10.42)
27 - Electrical equipment	6,342	(7.18)	49,680	(8.77)
28 - Machinery (n.e.c.)	17,383	(19.69)	103,593	(18.29)
29 - Motor vehicles	2,822	(3.20)	63,938	(11.29)
30 - Other transport equipment	1,738	(1.97)	25,120	(4.43)
31 - Furniture	1,439	(1.63)	2,542	(0.45)
32 - Other machinery	6,345	(7.19)	27,329	(4.82)
33 - Repair and installation of machinery	1,578	(1.79)	9,329	(1.65)
D - Electricity and gas	660	(0.38)	1,908	(0.21)
E - Water supply	880	(0.50)	1,131	(0.12)
F - Construction	6,115	(3.49)	10,407	(1.12)
G - Wholesale and retail trade	24,208	(13.80)	64,179	(6.93)
H - Transportation and storage	1,248	(0.71)	10,084	(1.09)
I - Accommodation	338	(0.19)	386	(0.04)
J - Information and communication	10,006	(5.70)	27,943	(3.02)
L - Real estate	1,683	(0.96)	4,057	(0.44)
M - Professional, scientific, technical activities	29,947	(17.07)	180,356	(19.48)
N - Administration	8,312	(4.74)	41,285	(4.46)
Q - Human health	1,344	(0.77)	3,484	(0.38)
R - Arts, entertainment	779	(0.44)	1,568	(0.17)
Total	175,457	(100.00)	925,989	(100.00)

Notes: The table displays the distribution of observations (N) in the main sample across sectors according to NACE Rev. 2 main categories. Note that initially all sectors were represented, but reasons of consistency, I exclude sectors K, O, P, S, T, and U. The absolute number of patents filed by firms in the corresponding sectors is also provided. The corresponding shares as fraction of total are indicated in parentheses next to respective values. The percentage on the subcategories of the manufacturing sector represent the share within the manufacturing sector, respectively patents filed by these firms.

Table A2: Correlation matrix patent measures

	Fwd. citations	Claims	Family size	Renewals	Incremental	Explorative
Fwd. citations	1.0000					
Claims	0.4313	1.0000				
Family size	0.0440	0.1724	1.0000			
Renewals	-0.0320	0.2440	0.0883	1.0000		
Incremental	-0.2066	-0.2050	-0.1160	0.0267	1.0000	
Explorative	0.2502	0.3315	0.0569	0.0349	-0.2199	1.0000

Table A3: List of FSAP Directives

Directive	**Name**	**Transposition date**
2000/46/EC	E-Money Directive*	27/04/2002
2000/64/EC	Directive on information exchange with 3^{rd} countries	17/11/2002
2001/17/EC	Directive on the reorganisation and winding up of insurance undertakings	20/04/2003
2001/97/EC	2^{nd} Money Laundering Directive*	15/06/2003
2001/107/EC	UCITS III - Directive (1)	13/08/2003
2001/108/EC	UCITS III - Directive (2)	13/08/2003
2002/83/EC	Solvency Margins Requirements Directive	20/09/2003
2002/13/EC	Solvency 1 Directive for non-life insurance	20/09/2003
2002/83/EC	Solvency 1 Directive for life insurance	20/09/2003
2002/47/EC	Financial Collateral Directive	27/12/2003
2003/48/EC	Savings Tax Directive*	01/01/2004
2001/65/EC	Fair Value Accounting Directive	01/01/2004
2001/24/EC	Directive on the reorganisation and winding up of credit institutions*	05/05/2004
2002/87/EC	Financial Conglomerates Directive*	11/08/2004
2002/65/EC	Distance Marketing Directive	09/10/2004
2001/86/EC	European Company Statute Directive	10/10/2004
2003/6/EC	Market Abuse Directive	12/10/2004
2003/51/EC	Modernisation Directive	01/01/2005
2002/92/EC	Insurance Mediation Directive	15/01/2005
2003/71/EC	Prospectus Directive	30/06/2005
2003/41/EC	Directive on the activities and supervision of IORP	23/09/2005
2004/25/EC	Takeover Bid Directive	20/05/2006
2006/48/EC	Capital Requirement Directive (1)*	31/12/2006
2006/49/EC	Capital Requirement Directive (2)*	31/12/2006
2004/109/EC	Transparency Directive	21/01/2007
2004/39/EC	Markets in Financial Instruments Directive (MiFID)	01/11/2007
2005/56/EC	Cross-Border Merger Directive	25/11/2007

Notes: The table lists the 27 FSAP Directives including a short description. Directives market with * are key FSAP measures affecting different banking sectors. Transposition dates refer to the intended implementation deadline set by the EU. Actual transposition dates significantly vary between countries. Individual dates are therefore not reported.

Table A4: Summary statistics, independent variables

Variable	**Definition**	**Obs.**	**Mean**	**Std. dev.**	**Min.**	**Max.**
Firm-level:						
Debt-ratio	$= \frac{debt}{ttl.\ assets}$	165,578	0.657	0.385	0	3.347
Intangibles	$= \frac{intangible\ assets}{fixed\ assets}$	164,054	0.170	0.287	0	1
Fixed assets	$= \frac{fixed\ assets}{ttl.\ assets}$	175,331	0.305	0.249	0	1
Firm age	= founding year − year	173,990	22.846	24.855	1	125
Profitability	$= ROA = \frac{profit/loss}{ttl.\ assets}$	127,577	0.024	0.170	-0.897	0.556
Cash-Flow	$= \frac{cash\ flow}{ttl.\ assets}$	117,008	0.080	0.147	-0.648	0.561
Macro-level:						
Economic conditions	GDP per capita	175,457	34.690	4.120	25.989	46.779
Productivity	Labour productivity (Output/hrs. worked)	175,457	47.871	5.312	34.220	59.530
Financial development	Banking sector Herfindahl-index	175,457	0.075	0.068	0.015	0.316
Business cycle	ECB financial distress indicator	175,457	0.119	0.079	0.024	0.556

Notes: The table lists the set of control variables, including the calculation method. Mostly, I omit the estimates on these control variables, but they are included in regressions whenever specified in the regression description. Age square is also included in all regression where firm-level controls are included. For precautious reasons, I include the control variables *profitability* and *cash flow* in regressions regarding bank debt and interest burden, because they might be confounding factors in those cases, resembling important demand- and supply-sided determinants.

Table A5: Robustness test using different definitions for the patent filing measure

Dependent variables:	Patent applications					
	Truncated		Normalized		Logarithm	
	(I)	(II)	(III)	(IV)	(V)	(VI)
FI × Exposure	1.416**	0.465**	0.063***	0.023***	0.035***	0.015***
	(0.604)	(0.206)	(0.013)	(0.004)	(0.009)	(0.004)
Additional controls:						
Firm-level	Yes	Yes	Yes	Yes	Yes	Yes
Firm-FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year-FE	Yes	Yes	Yes	Yes	Yes	Yes
Including zero values	No	Yes	No	Yes	No	Yes
Observations	33,858	87,992	33,858	87,992	33,858	87,992

Notes: This table presents estimates from panel regressions explaining patent filings. Regressions are repeated with varying definitions on the dependent variable, namely their truncated and normalized values, respectively the logarithm of the number of patent filings. Control variables as defined in Table A4 (Appendix D) are omitted but their usage is indicated in respective columns. Regressions are repeated imputing zero patents per firm as missing (Columns I, III, and V) or as true zeros (Columns II, IV, and VI). Standard errors (in parentheses below coefficients) are heteroscedasticity-consistent and clustered at the firm level. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table A6: Robustness test using different model specifications (patent quality)

	Patent quality					
Dependent variables:	Forward citations			Claims		
	(I)	(II)	(III)	(IV)	(V)	(VI)
FI	-0.008	0.004		-0.055**	-0.035**	
	(0.011)	(0.011)		(0.012)	(0.012)	
Exposure	-0.008*	0.002		-0.009*	0.009	
	(0.004)	(0.005)		(0.005)	(0.006)	
FI × Exposure		-0.028***	-0.032***		-0.048***	-0.048***
		(0.008)	(0.011)		(0.008)	(0.011)
Debt-ratio	-0.005	-0.005	-0.009	-0.003	-0.003	-0.003
	(0.004)	(0.004)	(0.008)	(0.004)	(0.004)	(0.009)
Intangibles	0.020***	0.020***	-0.018	-0.019***	-0.018***	-0.004
	(0.006)	(0.006)	(0.013)	(0.006)	(0.006)	(0.012)
Fixed assets	0.006	-0.005	-0.013	0.005	0.004	-0.000
	(0.006)	(0.006)	(0.013)	(0.007)	(0.007)	(0.015)
Age	-0.000**	-0.000**	-0.001	-0.000	-0.000	-0.002**
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)
Constant	-0.066	-0.056	-0.136***	0.000	-0.001	0.000
	(0.041)	(0.041)	(0.037)	(0.001)	(0.001)	(0.001)
Additional controls:						
Macro-level	Yes	Yes	No	Yes	Yes	No
Country-FE	Yes	Yes	No	Yes	Yes	No
Industry-FE	Yes	Yes	No	Yes	Yes	No
Firm-FE	No	No	Yes	No	No	Yes
Country-Year-FE	No	No	Yes	No	No	Yes
Observations	22,784	22,784	22,784	22,784	22,784	22,784

Notes: This table presents estimates from panel regressions explaining different measures of patent quality. The patent-related measures are forward citations (Columns I-III), and the number of claims (Columns IV-VI). The main variable of interest is the difference-in-difference estimator. All variables are specified as above defined. Estimates on controls are omitted but their usage is indicated in respective columns. Standard errors (in parentheses below coefficients) are heteroscedasticity-consistent and clustered at the firm level. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table A7: Robustness test using different model specifications (patent value)

Dependent variables:	Patent value					
	Family size			Renewals		
	(I)	(II)	(III)	(IV)	(V)	(VI)
FI	-0.018*	-0.013		-0.024**	-0.027***	
	(0.011)	(0.011)		(0.010)	(0.010)	
Exposure	-0.003	0.002		-0.015**	- 0.018***	
	(0.006)	(0.006)		(0.011)	(0.005)	
FI $\times$ Exposure		-0.012	-0.021**		0.008	-0.004
		(0.008)	(0.010)		(0.023)	(0.009)
Debt-ratio	-0.001	-0.001	-0.003	-0.003	-0.003	0.002
	(0.004)	(0.004)	(0.006)	(0.002)	(0.002)	(0.006)
Intangibles	0.022***	0.022***	-0.018	-0.006	-0.006	-0.024**
	(0.007)	(0.007)	(0.005)	(0.005)	(0.005)	(0.011)
Fixed assets	0.022***	0.022***	-0.023***	0.000	0.000	-0.004
	(0.007)	(0.007)	(0.011)	(0.006)	(0.006)	(0.013)
Age	0.000*	0.000*	-0.002**	0.000**	0.000**	0.000
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)
Constant	0.083*	0.088*	-0.356***	0.224***	0.221***	0.105**
	(0.045)	(0.045)	(0.031)	(0.040)	(0.040)	(0.043)
Additional controls:						
Macro-level	Yes	Yes	No	Yes	Yes	No
Country-FE	Yes	Yes	No	Yes	Yes	No
Industry-FE	Yes	Yes	No	Yes	Yes	No
Firm-FE	No	No	Yes	No	No	Yes
Country-Year-FE	No	No	Yes	No	No	Yes
Observations	22,784	22,784	22,784	22,784	22,784	22,784

Notes: This table presents estimates from panel regressions explaining different measures of patent value. The patent-related measures are family size (Columns I-III), and patent renewals (Columns IV-VI). The main variable of interest is the difference-in-difference estimator. All variables are specified as above defined. Estimates on controls are omitted but their usage is indicated in respective columns. Standard errors (in parentheses below coefficients) are heteroscedasticity-consistent and clustered at the firm level. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table A8: Robustness test using different model specifications (patent types)

Dependent variables:	Patent types					
	Incremental			Explorative		
	(I)	(II)	(III)	(IV)	(V)	(VI)
FI	0.033***	-0.026**		-0.030***	-0.025**	
	(0.012)	(0.012)		(0.010)	(0.010)	
Exposure	-0.000	-0.007		-0.008***	-0.004	
	(0.005)	(0.006)		(0.003)	(0.004)	
FI × Exposure		0.018**	0.021*		-0.012*	-0.019**
		(0.008)	(0.011)		(0.006)	(0.009)
Debt-ratio	0.002	0.002	0.008	-0.003	-0.003	-0.005
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.005)
Intangibles	-0.014**	-0.014**	-0.014	0.007	0.007	0.034***
	(0.007)	(0.007)	(0.013)	(0.005)	(0.005)	(0.012)
Fixed assets	-0.017**	-0.017**	-0.019	-0.004	-0.004	-0.011
	(0.007)	(0.007)	(0.013)	(0.005)	(0.005)	(0.012)
Age	0.000	0.000	-0.001	0.000	0.000	0.000
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)
Constant	0.656***	0.649***	-0.450***	0.126**	0.131***	0.034
	(0.046)	(0.046)	(0.034)	(0.031)	(0.050)	(0.022)
Additional controls:						
Macro-level	Yes	Yes	No	Yes	Yes	No
Country-FE	Yes	Yes	No	Yes	Yes	No
Industry-FE	Yes	Yes	No	Yes	Yes	No
Firm-FE	No	No	Yes	No	No	Yes
Country-Year-FE	No	No	Yes	No	No	Yes
Observations	22,784	22,784	22,784	22,784	22,784	22,784

Notes: This table presents estimates from panel regressions explaining different measures of patent types. The patent-related measures are the share of incremental (Columns I-III) and explorative patents (Columns IV-VI). The main variable of interest is the difference-in-difference estimator. All variables are specified as above defined. Estimates on controls are omitted but their usage is indicated in respective columns. Standard errors (in parentheses below coefficients) are heteroscedasticity-consistent and clustered at the firm level. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table A9: Financial integration and patenting: testing different exposure thresholds

	Patent quality		Patent value		Patent types	
Dependent variables:	Forward citations	Claims	Family size	Renewals	Incremental	Explorative
	(I)	(II)	(III)	(IV)	(V)	(VI)
FI × Exposure (Q50)	-0.032***	-0.048***	-0.021**	-0.004	0.021*	-0.019**
	(0.011)	(0.011)	(0.010)	(0.009)	(0.011)	(0.009)
FI × Exposure (Q33)	-0.033**	-0.053***	-0.029**	-0.004	0.032**	-0.022*
	(0.014)	(0.016)	(0.013)	(0.011)	(0.015)	(0.012)
FI × Exposure (Q25)	-0.048***	-0.055***	-0.039**	0.000	0.040**	-0.023
	(0.018)	(0.019)	(0.017)	(0.013)	(0.018)	(0.014)
Additional controls:						
Firm-level	Yes	Yes	Yes	Yes	Yes	Yes
Firm-FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year-FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table displays regression results from the baseline specification as defined in Equation (2). The dependent variables are previously specified patent quality (Columns I-II) and value-related (Columns III-IV) dimensions as well as different patent types (Columns V-VI). Regressions are repeated with varying definitions on the indicator on whether a firm can be considered as affected (= 1) or not (= 0), i.e. using varying cutoff thresholds q50 (Row1), q33 (Row2), q25 (Row 3) according to which firms can be considered as financially constrained. Control variables are in accordance with the baseline regressions. Coefficients are not displayed but their usage is indicated in respective columns. Standard errors (in parentheses below coefficients) are heteroscedasticity-consistent and clustered at the firm level. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table A10: Panel regressions: maximum values of patent measures

Dependent variable:	Forward citations	Claims	Family size	Renewals
	(I)	(II)	(III)	(IV)
FI × Exposure	-0.033***	0.034	-0.017*	0.009*
	(0.009)	(0.023)	(0.009)	(0.005)
Additional controls:				
Firm-level	Yes	Yes	Yes	Yes
Firm-FE	Yes	Yes	Yes	Yes
Country-Year-FE	Yes	Yes	Yes	Yes

Notes: This table presents estimates from panel regressions explaining the maximum values of respective patenting measures. Estimations are analogous to the baseline specification in Equation (2), only the definition of the dependent variable is adjusted. Instead of taking the firm-years specific average of each measure, the maximum value is chosen. Control variables are in accordance with the baseline regressions. Coefficients are not displayed but their usage is indicated in respective columns. Standard errors (in parentheses below coefficients) are heteroscedasticity-consistent and clustered at the firm level. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table A11: Robustness test using the originality index as alternative definition of patent types

Dependent variables:	Originality Index					
	(I)	(II)	(III)	(IV)	(V)	(VI)
FI	-0.029*	-0.006		-0.037**	-0.018	
	(0.017)	(0.018)		(0.016)	(0.017)	
Exposure	0.010	0.031***		0.007	0.025***	
	(0.008)	(0.009)		(0.007)	(0.004)	
FI $\times$ Exposure		-0.056***	-0.039**		-0.046***	-0.036**
		(0.012)	(0.016)		(0.012)	(0.015)
Debt-ratio	0.000	-0.000	-0.005	0.003	0.002	-0.010
	(0.006)	(0.006)	(0.011)	(0.006)	(0.006)	(0.011)
Intangibles	0.014	0.013	0.012	0.017*	0.017*	0.012
	(0.010)	(0.010)	(0.020)	(0.010)	(0.010)	(0.019)
Fixed assets	-0.002	-0.002	0.021	0.003	0.002	0.023
	(0.011)	(0.011)	(0.022)	(0.011)	(0.011)	(0.021)
Age	-0.000*	-0.000*	-0.000	-0.000*	-0.000*	-0.000
	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.002)
Constant	-0.036	-0.014	0.345***	-0.081	-0.063	0.286***
	(0.069)	(0.069)	(0.072)	(0.063)	(0.063)	(0.065)
Additional controls:						
Macro-level	Yes	Yes	No	Yes	Yes	No
Country-FE	Yes	Yes	No	Yes	Yes	No
Industry-FE	Yes	Yes	No	Yes	Yes	No
Firm-FE	No	No	Yes	No	No	Yes
Country-Year-FE	No	No	Yes	No	No	Yes
Observations	22,784	22,784	22,784	22,784	22,784	22,784

Notes: This table presents estimates from panel regressions explaining different measures of patent types. The patent-related variables are two specific measures of the originality index as defined by Hall *et al.* (2001). They refer to the degree to which firms' patents are only a basic invention, i.e. lower scores reflect minor inventive steps (vice versa). The index is based on the number and distribution of cited IPC classes and can be defined based on IPC 8-digit categories (Columns I-III) as well as IPC 4-digit categories (Columns IV-VI). The main variable of interest is the difference-in-difference estimator. All variables are specified as above defined. Estimates on controls are omitted but their usage is indicated in respective columns. Standard errors (in parentheses below coefficients) are heteroscedasticity-consistent and clustered at the firm level. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table A12: Testing different lag-levels of the main regressor

Category:	Patent quality		Patent value		Patent types	
Dep. variables:	Forward cits.	Claims	Family size	Renewals	Incremental	Explorative
$FI_t \times$ Exposure	-0.014*	-0.012	-0.012*	0.010	-0.014*	-0.008
	(0.008)	(0.008)	(0.007)	(0.007)	(0.008)	(0.006)
$FI_{t-1} \times$ Exposure	-0.032***	-0.048***	-0.021**	-0.004	0.021*	-0.019**
	(0.011)	(0.011)	(0.010)	(0.009)	(0.011)	(0.009)
$FI_{t-2} \times$ Exposure	0.043***	0.079***	-0.011**	0.004	-0.044**	-0.024*
	(0.015)	(0.017)	(0.035)	(0.012)	(0.015)	(0.014)
$FI_{t-3} \times$ Exposure	0.037*	0.044**	-0.027	0.014	-0.070***	-0.015
	(0.021)	(0.022)	(0.019)	(0.015)	(0.022)	(0.020)

Notes: This table presents estimates on the correlation coefficients of the interaction terms of the exposure variable with the main regressor, the integration-index FI_{ct}. Regressions are repeated using different lag levels of the main regressor, namely the contemporaneous level as well as the one, two, and three year lags. For the sake of visualization, all remaining variables and coefficients are omitted. The dependent variables include all relevant patent dimensions as defined above. The model setup is equivalent to the baseline regression as defined in Equation (2). Standard errors (in parentheses) are heteroscedasticity-consistent and clustered at the firm level. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table A13: Average values of the integration measure over the years relative to FSAP initiation

	Financial integration value						
	$t=0$	$t=1$	$t=2$	$t=3$	$t=4$	$t=5$	$t=6$
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
FI	–	0.121	0.271	0.428	0.643	0.777	0.980

Notes: This table displays the average value of the FI_{ct} integration measure for the country-specific years relative to the first year where $FI_{ct} > 0$. Note that the displayed values are averages over all countries at a country-specific time and not a specific year.

Table A14: Heterogeneity across firms: manufacturing versus non-manufacturing firms

Dependent variables:	Forward cits. (I)	Family size (II)	Incremental (III)	Explorative (IV)
	Panel A: Manufacturing sector			
FI × Exposure	-0.050*** (0.015)	-0.033*** (0.013)	0.037*** (0.014)	-0.021* (0.012)
Controls:				
Firm-level	Yes	Yes	Yes	Yes
Firm-FE	Yes	Yes	Yes	Yes
Country-Year-FE	Yes	Yes	Yes	Yes
Observations	13,503	13,503	13,503	13,503
	Panel B: Non-manufacturing sectors			
FI × Exposure	-0.010 (0.015)	-0.004 (0.015)	0.000 (0.016)	-0.016 (0.014)
Additional controls:				
Firm-level	Yes	Yes	Yes	Yes
Firm-FE	Yes	Yes	Yes	Yes
Country-Year-FE	Yes	Yes	Yes	Yes
Observations	9,281	9,281	9,281	9,281

Notes: This table presents estimates on the coefficients of the interaction terms deployed as in previous regressions (see Table 5). Results are retrieved from the baseline regression model as defined in Equation (2) but the sample is split according to the sectoral affiliation, i.e. whether a firm is affiliated to the manufacturing sector (Panel A) or not (Panel B). All remaining variables and coefficients are omitted and only one of the variables per quality and market value category is displayed. The dependent variables include relevant patent specified above. Standard errors (in parentheses) are heteroscedasticity-consistent and clustered at the firm level. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table A15: Robustness test using different definitions for bank loans

Dependent variables:	Bank loan			
	Logarithm (I)	Asset-ratio (II)	Liability-ratio (III)	Total debt (IV)
FI × Exposure	0.270*** (0.072)	0.005** (0.002)	0.009** (0.004)	0.057*** (0.022)
Additional controls:				
Lagged dependent variable	Yes	Yes	Yes	Yes
Firm-level	Yes	Yes	Yes	Yes
Firm-FE	Yes	Yes	Yes	Yes
Country-Year-FE	Yes	Yes	Yes	Yes
Observations	47,538	47,538	43,789	52,107

Notes: This table presents estimates from panel regressions explaining bank loans. Bank loans are defined as the logarithm of total loans (Columns I), total loans to asset ratio (Column II), total loans to liabilities ratio (Column III). Column IV measures the logarithm of total debt as dependent variable. Regressions are analogue to those specified in Equation (2) using control variables defined in Table A4 (Appendix D). Coefficients on these control variables are not displayed but their usage is indicated in respective columns. Standard errors (in parentheses below coefficients) are heteroscedasticity-consistent and clustered at the firm level. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table A16: Robustness test using different definitions for interest burden

Dependent variables:	Interst burden			
	Avg. loan-ratio	Liability-ratio	Logarithm	Financial expenses
	(I)	(II)	(III)	(IV)
FI × Exposure	-2.465***	-0.316**	-0.174***	-1.608
	(0.772)	(0.138)	(0.033)	(1.279)
Additional controls:				
Lagged dependent variable	Yes	Yes	Yes	No
Firm-level	Yes	Yes	Yes	Yes
Firm-FE	Yes	Yes	Yes	Yes
Country-Year-FE	Yes	Yes	Yes	Yes
Observations	27,652	38,913	37,899	32,576

Notes: This table presents estimates from panel regressions explaining firms' borrowing conditions. Regressions are repeated with varying definitions on the dependent variable, using alternative definitions of firms' interest burden, namely ratio of interest payments over *average* loans during the period (Column I), interest payments as a ratio of total liabilities (Column II), the first difference of the logarithm of total interest payments as dependent variable, and the ratio of total financial expenses over loans ratio (Column IV). Control variables as defined as in the baseline regressions from Equation (2) – only in Column IV the lagged value of the dependent variable is not used as control due to the use of first-differences. Coefficients on controls are not displayed but their usage is indicated in respective columns. Standard errors (in parentheses below coefficients) are heteroscedasticity-consistent and clustered at the firm level. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table A17: Financial integration, borrowing, and its costs: testing different exposure thresholds

Dependent variable:	Bank loan ratios			Interest burden		
	(I)	(II)	(III)	(IV)	(V)	(VI)
FI × Exposure (Q50)	0.270***			-2.465***		
	(0.072)			(0.772)		
FI × Exposure (Q33)		0.360***			-2.951***	
		(0.073)			(1.045)	
FI × Exposure (Q25)			0.345***			-5.151***
			(0.080)			(1.323)
Additional controls:						
Lagged dependent variable	Yes	Yes	Yes	Yes	Yes	Yes
Firm-level	Yes	Yes	Yes	Yes	Yes	Yes
Firm-FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year-FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	47,538	51,148	54,680	27,652	30,837	33,268

Notes: This table presents estimates from panel regressions explaining the logarithm of bank loans (Columns I-III) and interest charges as a fraction of total bank loans (Columns IV-VI), respectively. Regressions are repeated with varying definitions on the indicator on whether a firm can be considered as exposed to the treatment (= 1) or not (= 0), i.e. using varying cutoff thresholds q50 (Column I and IV), q33 (Column II and V), q25 (Column III and VI) according to which firms can be considered as financially constrained. Control variables are in accordance with the baseline regressions. Coefficients are not displayed but their use is indicated in respective columns. Standard errors (in parentheses below coefficients) are heteroscedasticity-consistent and clustered at the firm level. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table A18: Placebo regressions: patent quality and value

Dependent variables:	Patent quality		Patent value		Patent types	
	Forward Citations	Claims	Family size	Renewals	Incremental	Explorative
	(I)	(II)	(III)	(IV)	(V)	(VI)
Placebo results:						
FI × Exposure	0.011	0.029**	0.009	0.028	-0.024	-0.010
	(0.008)	(0.011)	(0.013)	(0.074)	(0.020)	(0.011)
Baseline results:						
FI × Exposure	*-0.032****	*-0.048****	*-0.021***	*-0.004*	*0.021**	*-0.019***
	(0.011)	*(0.011)*	*(0.010)*	*(0.009)*	*(0.011)*	*(0.009)*
Additional controls:						
Firm-level	Yes	Yes	Yes	Yes	Yes	Yes
Firm-FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year-FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,700	12,700	12,700	12,700	12,700	12,642

Notes: This table presents estimates from panel regressions repeating the baseline regressions in the placebo setup (1997-2004) as described in Appendix C. The main variable of interest is the DID-estimator, i.e. the interaction of FI_{ct} and Exposure, which are defined in Equation (2). Regression specifications include firm- and country-year fixed effects as well as the lagged dependent variable. Respective coefficients are omitted but their use is indicated in the columns. For illustrative purposes, the corresponding correlation coefficients of the baseline regressions (Table 5) are displayed in shaded gray below the coefficient of interest. Standard errors (in parentheses below coefficients) are heteroscedasticity-consistent and clustered at the firm level. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

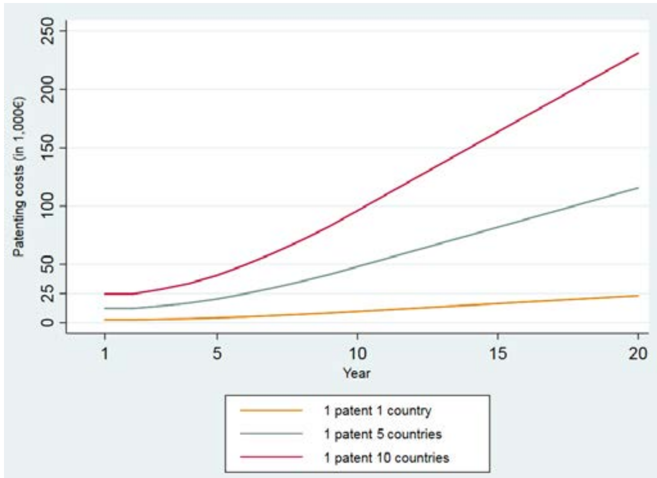
Table A19: Panel regressions: beneficiaries and bank borrowing

Dependent variables:	Bank loans			
	(I)	(II)	(III)	(IV)
FI × Exposure	0.270***	-0.080	0.005**	-0.008
	(0.072)	(0.128)	(0.002)	(0.008)
FI × Exposure × Beneficiary		0.475***		0.027***
		(0.134)		(0.008)
Additional controls:				
Lagged dependent variable	Yes	Yes	Yes	Yes
Firm-level	Yes	Yes	Yes	Yes
Firm-FE	Yes	Yes	Yes	Yes
Country-Year-FE	Yes	Yes	Yes	Yes
Observations	47,538	29,546	43,789	29,546

Notes: This table presents estimates from panel regressions explaining bank loans. Regressions are repeated with varying definitions on the dependent variable, using alternative definitions of bank loans, namely the logarithm of total loans (Columns I and II) as well as the bank loan to asset ratio (Columns III and IV). In Columns II and IV, the interaction term is additionally interacted with the beneficiary dummy, which is a time-invariant indicator equal to one if the average interest burden during the post integration phase, i.e. when the country-specific integration measure $FI_{ct} > 0.66$, is lower as compared to the average across the entire timeframe. Control variables as defined as in the baseline regressions. Coefficients on controls are not displayed but their usage is indicated in respective columns. Standard errors (in parentheses below coefficients) are heteroscedasticity-consistent and clustered at the firm level. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

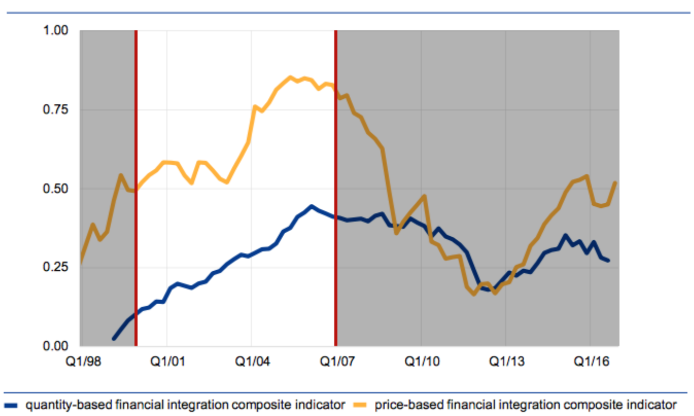
Appendix E: Figures (A1-A5)

Figure A1: Cumulative costs incurring from patent renewals (at multiple patent offices)



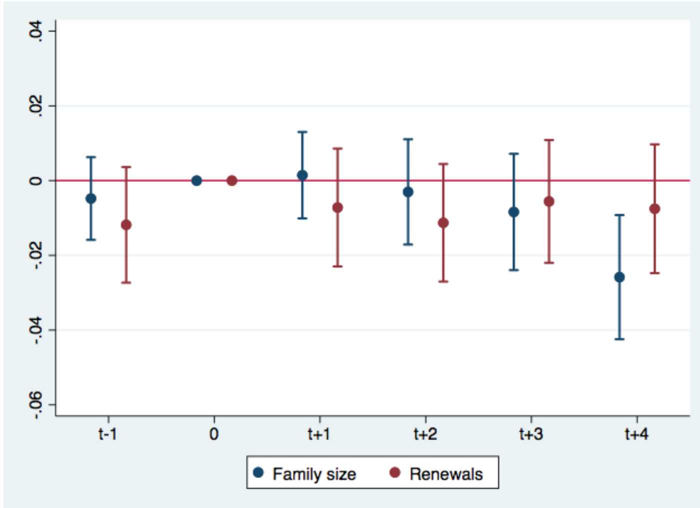
Notes: This figure sketches the cumulative costs for a patent kept alive for a given number of years with a maximum of 20 years. Costs are calculated based on the *schedule of fees* from the EPO valid on December 31st, 2008. For the sake of comparability, initial costs are included, which comprise fees for the online application (100 Euro), examination (1,405 Euro), and grant (790 Euro) of the patent. Note, these costs are standard components but overall application costs may vary according to different specifications.

Figure A2: Aggregate statistics: ECB financial integration measures



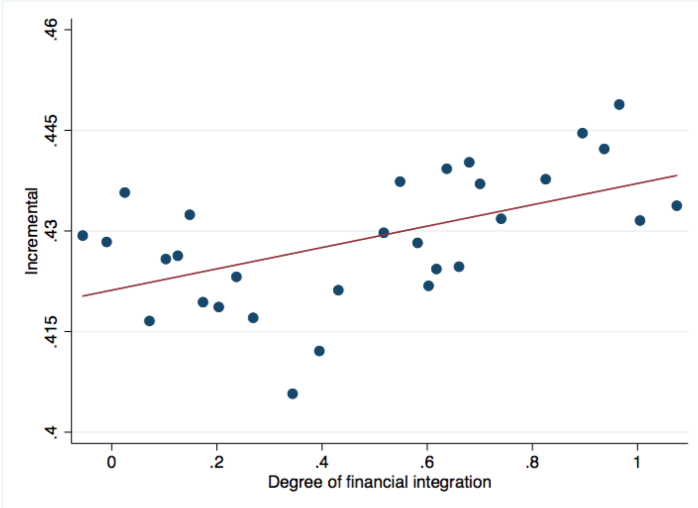
Notes: The figure drafts two measures of financial integration as defined by the European Central Bank (2016) between 1998 and 2016 and highlights the sample time frame (2000-2008). The blue line resembles ECB's quantity-based composite indicator measuring monetary financial insitutions' (MFI) loans to non-financial corporations. The yellow line resembles ECB's price-based composite indicator measuring standard deviations of MFI interest rates on new loans to non-financial corporations and households.

Figure A3: Coefficient plot: the lagged impact of financial integration on patent value



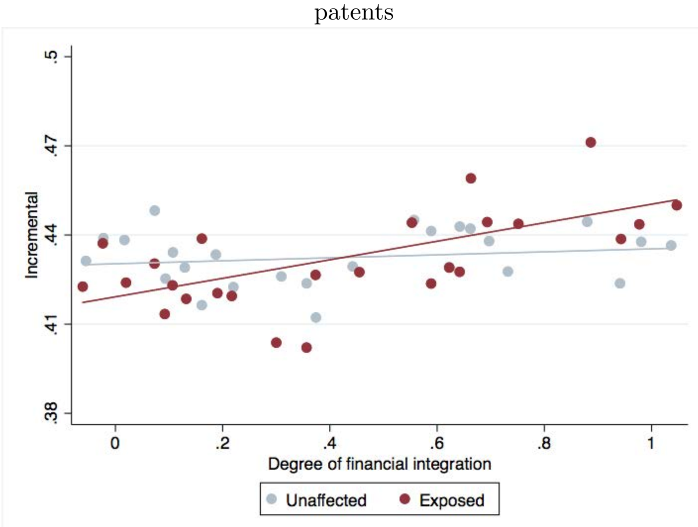
Notes: This table plots the regression coefficients of the interaction terms of the exposure variable with a set of time dummies. All specifications from Figure 4 apply. The dependent variables are normalized values of either family size or patent renewals.

Figure A4: FSAP measure and patenting: the share of incremental patents



Notes: This binned scatterplot illustrates the relationship between the FI_{ct} measure as defined in Equation (1) and patenting activities, which are plotted on the x- and y-axis, respectively. In this case, patenting refers to the share of incremental patents among all patents filed within the respective year. The number of bins is 30.

Figure A5: Patenting, integration and ex ante constrained firms: the share of incremental patents



Notes: This binned scatterplot illustrates the relationship between the FI_{ct} measure as defined in Equation (1) and patenting activities, which are plotted on the x- and y-axis, respectively. In this case, patenting refers to the share of incremental patents among all patents filed within the respective year. The sample is split according to ex ante constrained (red) and unconstrained firms (gray), i.e. firms exposed to and unaffected by the treatment. The number of bins for each group is 25.