Borrowing against the (Un)Known: Patent Portfolios and Leverage*

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Abstract

This paper analyses the importance of intellectual property in determining capital structure decisions. By exploiting a change in EU-law, we causally show that larger and more valuable patent portfolios lead to higher debt-ratios. Furthermore, linking highly disaggregated patenting data to firms' financials allows us to document heterogeneous effects across industry and patent characteristics. Our results provide evidence that stronger intellectual property rights enforcement benefit innovation-intense firms that are financially constrained.

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1 Introduction

Capital structure decisions are often accompanied by severe agency costs. Especially for debt financing, these frictions can lead to higher refinancing costs, lower levels of investment and credit rationing, all of which are harmful to firm value. One obvious solution to these problems is to provide securities, which usually take the form of tangible assets (Shleifer and Vishny 1992, Morellec 2001). More recently, however, evidence indicates that intangibles can support debt financing to a similar degree as tangible assets, despite inherent opacity and high valuation risk (Chava *et al.* 2017, Farre-Mensa *et al.* 2017, Mann 2018).

Studying the role of patents is a promising venue to measure the impact of one specific intangible assets, intellectual property rights (IPR), on firms' capital structure decision. First, by nature, patents act as a securitization of future cash flows because they grant a monopoly right to its owner to appropriate future returns. Importantly, Lian and Ma (2019) show that 80 percent of US non-financial firms' debt is based on their expected future cash flows from operations and not based on specific assets.[1] If firms predominantly borrow against future revenues, intellectual property can relax borrowing constraints by informing investors about future performance and by signaling prospective cash flows. Accordingly, patenting should be well suited to increase the debt capacity on a firm-level – even without being explicitly pledged as collateral.

Second, IPR gain a certain degree of asset tangibility, if they are protected by a patent. Patenting activities are a thoroughly documented dimension of firms' intangible property and can be quantified reliably. This enables potential lenders to assess respective firms' inventive activities, which should help mitigate borrowing constraints.

In this paper, our objective is therefore to investigate whether patents indeed increase the debt capacity of firms and thereby firms' individual leverage ratios. Exploiting exogenous variation in patent value arising from the staggered implementation of a major legal amendment, we show that a higher valuable patent portfolio causally increases firms' leverage ratios by lowering their interest burden, when controlling for common capital structure determinants as well as time and firm fixed effects. An increase of one standard deviation in the patenting measure translates to a 8.6 percent increase in the average firm's debt to asset ratio. In addition, specific characteristics of both the patent stock as well as the patentee affect this relationship. First, the overall size and market value of patent stocks are crucial in determining leverage. Second, more general patent portfolios relating to a broader set of technology classes have a larger effect as compared to more technologically specific patent stocks. Third, the most affected are firms active in industries with a high patenting propensity, i.e. in which patenting is likely considered as a common business strategy. Finally, we show that large and valuable patent stocks lead to lower interest payments. Moving from the median to the 90^{th}-percentile of the patent stock distribution translates to an 8.3 percent average decrease in the interest burden. Using the same identification strategy, we therefore provide a causal link between firms' patenting activity and their debt capacity.

[1] In fact, Mann (2018) finds that patenting enhances firms' debt capacity by being explicitly pledged as collateral. In this case, however, debt is secured in the form of asset-based lending.

To obtain these results, in our empirical estimations we use a staggered legislative change in EU-law, the Enforcement Directive (2004/48/EC), as an identifying event. This legislative change exogenously increased patent value during the mid-2000s across all member states by harmonizing and improving enforcement of IPR.

In addition, we use a unique data set combining in-depth legal European patent data (PATSTAT) with companies balance sheet data (Amadeus) across several European countries and industries over a time span of 12 years. These features allow us to disentangle heterogeneity in patenting activities and to pin down distinct drivers of the relationship between patenting and leverage by exploiting variation across industries and firms. Furthermore, our setup enables us to exploit a valuable feature in the European patent system: obligatory renewal payments. By tracking these annual payments, we can precisely map the actual size and value of firms' patent portfolios for each year.

Our analysis contributes and extends previous research in multiple ways. First, we are able to assess the effect of intellectual property on the most common mode of obtaining debt, i.e. via cash flow based lending. Second, to the best of our knowledge, we are the first who can analyze the role of actively held patent portfolios on firms' capital structure decisions. This approach appears promising, because the patent stock is likely to represent a more accurate measure of firms' intellectual property than other (patent-related) approximations. Third, we can control and observe heterogeneous effects arising from patent- as well as firm-specific characteristics. In fact, we can show that both quantitative and qualitative characteristics of the patent portfolio are decisive in determining how patent portfolios affect leverage. In this context, the value of the patent stock is a stronger determinant of leverage compared to patent filings or simple quantitative measures of patent stocks. Thus, our measures allow us to shed new light on companies' optimal capital structure decision. Finally, our results suggest that enhancing enforcement rules across different jurisdictions benefits innovating firms, which are often have difficulties accessing debt funding.

A fundamental empirical challenge is to quantify intangibles appropriately. Early analyses on the topic try to overcome measurement issues by focusing exclusively on externally acquired intangible assets, e.g. in the process of firm acquisitions or liquidations. In the course of the acquisition, intangible assets become part of the acquirer's balance sheet and can be measured reliably. In contrast, *internally* generated intangibles, such as patents, trademarks, or brands, are not captured by common accounting practices, even though they constitute the vast majority of total intangibles. A recent study by Peters and Taylor (2017) shows that more than 80 percent of intangibles are generated internally and not through acquisition.

We propose a novel and, from our point of view, more convincing way to quantify intangible property. We measure intangibles by the size and value of the entire stock of *active* patents a firm holds at a given point in time – the firm's patent portfolio. This approach has several distinct advantages. First, we capture internally generated intangibles of a firm, which represent the majority of total intangible assets. Second, applying patent data allows us to assess more characteristics of the underlying invention. We can therefore paint a nuanced picture of the drivers that link intellectual property to firms' financial leverage. Third, using actively held stocks for the measurement of firm-level patenting is superior to the use of filings or grants. Patent applications do not necessarily account for whether a patent is actually granted. Similarly, patent grants do not account for whether patents are actually held, i.e. remain the intellectual property of a firm for any year after granting. In fact, aggregate statistics show that only 20 percent of firms hold their patent over the maximum length (Harhoff 2016).

Due to specific features both in our data structure and in the institutional setup, we are able to measure the size as well as other quantitative and qualitative aspects of patent portfolios for firms of different nationalities across many years. Unlike in other jurisdictions, European patent holders decide actively whether to prolong the life of i) each individual patent, ii) in each individual country, and iii) in *every year* by submitting maintenance fees to respective patent offices. These annual payments allow us to identify if and in how many jurisdictions firms' patents are active. In comparison, in the US patent system, renewal fees are due only three times over the course of 20 years after application. The EU regulatory regime enables a more reliable and precise quantification of the size and value of firms' IPR over time.

In order to address endogeneity concerns, we follow a multilayered approach. First, we measure the impact of the patent portfolio at the beginning of each year on the leverage decision at the end of the year. This should soften reverse-causality issues. Second, we show that effects are heterogeneous with regard to different firm and patent characteristics. Third, in the empirical analysis, we explore the staggered implementation of the European Commission's Enforcement Directive (2004/48/EC) across EU member states, to evaluate the causal impact of varying patents values on financial leverage. The identifying event leads to an exogenous increase in the value of IPR across all firms. Fourth, we can show that large and valuable patent stocks lead to lower costs of obtaining external funding, i.e. lower interest burden on outstanding debt. This is a plausible mechanism of how higher valued patent portfolios could enable firms to increase their debt capacity and hence their leverage.

Our study relates mainly to three branches of literature. First, our paper adds to the literature on optimal capital structure decisions of firms. Since the seminal work by Modigliani and Miller 1958 and 1963 there has been a wide range of papers studying firms' optimal capital decisions.[2] Besides one strand of empirical literature, which mostly test either the trade-off-theory or the pecking order theory (see e.g. Fama and French 2002, Frank and Goyal 2003), many papers - such as ours - focus on capital structure determinants either across countries, time, or industries (see e.g. Hall *et al.* 2004, Lemmon *et al.* 2008).

Second, we contribute to the literature on financial constraints, i.e. of innovation-based firms. Hall (2002) finds R&D-intensive firms to be considerably less leveraged as compared to other firms; an observation confirmed in our data. There are several inherent reasons why inventive firms face difficulties in obtaining debt finance.[3] Leaving these firms particularly exposed to financing

[2]See e.g. Myers and Majluf (1984), Jensen and Meckling (1976) and Rajan and Zingales (1995).

[3]First, debt contract structures are not well suited for research-intensive firms with uncertain and volatile returns (Stiglitz 1985). Second, adverse selection problems are more likely in high-tech industries (Stiglitz and Weiss 1981).

constraints therefore restricts R&D, hence inventive activities, much more than other forms of investment. Compared to the vast literature testing for the presence of these constraints on capital investment, we focus on inventive activities as a mean for innovation-based firms to eliminate them.

Third and most notably, our paper relates directly to analyses on the use of intellectual property for obtaining outside funding, in particular debt financing. The role of collateral in funding decisions is widely discussed in the literature.[4] The use of easy to liquidate, *tangible* assets is conventionally considered the prime mode for collateralization, which helps circumventing agency issues between borrowers and lenders (Shleifer and Vishny 1992, Morellec 2001, Rampini and Viswanathan 2013). An evolving strand of literature, however, explores the use of intangibles in this context. For example, Loumioti (2012) estimates that the use of intangible assets securing syndicated loans increased from 11 percent in 1997 to 24 percent in 2005. With regard to patenting, research shows that this type of IPR enhances access to both equity as well as debt finance by reducing information asymmetries via signaling (Haeussler *et al.* 2014, Saidi and Zaldokas 2017), lowering spreads on bank loans (Chava *et al.* 2017) or being pledged as collateral to raise debt financing (Mann 2018). Studying the market for venture lending, Hochberg *et al.* (2018) show that about one out of four US-based start-ups utilize patents as collateral in debt contracts. In a more general assessment, Farre-Mensa *et al.* (2017) argue that obtaining a patent facilitates access to various external funding sources causally for young firms.

Closest to our paper is the work by Mann (2018), who studies how patents are explicitly included in loan contracts. By exploiting court decisions, the author shows that patenting companies raise more debt and spent more on R&D when creditor rights strengthen. Considering the entire distribution of firms, the author estimates that 38 percent of patenting firms in the US have used their patents for securing debt at least once in their firm history. Our study focuses on a complementary effect IPR can have regarding firms' capability to attract debt financing. Since corporate debt is predominantly secured via cash flow based lending (Lian and Ma 2019), we argue that the main effect of patents arises from owning them but not necessarily by pledging them explicitly. Further, in contrast to Mann (2018), our sample is not limited to large, public firms but consists of mainly small firms. It is therefore less likely that the effects of IPR on firms' debt capacity are biased with regard to a simultaneous use of other tangible assets. As such, large firms commonly have more tangible assets which might be used complementarily to their stock of intangibles.

The remainder of the paper is organized as follows. The next section outlines the institutional background of our study by discussing the role of patents in the context of borrowing activities and their actual utilization for external financing purposes[5], before introducing our hypotheses which build on previous theoretical and empirical evidence. In the third section, we introduce our data set and provide descriptive statistics on our sample. In the fourth section we present our empirical

Third, debt financing can lead to ex post changes in behavior that are likely more severe for high-tech firms. Fourth, the expected marginal cost of financial distress rises rapidly with leverage of inventive firms (Cornell and Shapiro 1988). Finally, the limited collateral value of intangible assets restricts the use of debt (Berger and Udell 2006).

[4]For a comprehensive overview, see Graham and Leary (2011).

[5]Here we cover the *de facto* implementation from an economic perspective. Similarly important, though beyond the scope of our analysis, is the legal - or *de jure* - perspective on how to potentially deploy patents in loan contracts. For a brief summary on this issue, see Appendix A.

results. The last section concludes.

2 Institutional background and hypotheses

2.1 Intellectual property and external debt

Intellectual property rights are designed for their owners to allow appropriation of returns from their investment in intangible assets. Just like tangible property, they carry inherent value and frequently constitute a substantial part of overall firm value. At the same time, only a small fraction of inventions protected by IPR are economically successful, whereas the majority is of little or no value. This makes it very hard to predict success or assign market values to IPR ex ante.

Patents as one specific form of IPR are exclusive rights on products or processes that provide new technical solutions to a problem. Moreover, patents can be viewed as a valuable source of information for a variety of different parties, such as business partners or competitors. Most important for our analysis, this also includes (potential) investors and loan providers. Thus, informational asymmetries are less of a concern regarding firms' patented inventions, because each patent is fully disclosed after publication. Even though the assessment of patent value is not trivial[6] recent findings emphasize the importance of patenting for supporting firms' debt capacity. The mitigating characteristics of IPR to attract external funding thus apparently apply for patented inventions to a minor extent.

There are two ways in which firms may actually use their patent portfolio to support external debt financing: directly (asset-based lending) and indirectly (cash flow-based lending). With respect to explicit use, patents might be directly used to collateralize loans. For example, Mann (2018) shows that firms pledge patents as collateral allowing them to increase their debt capacity. To illustrate that this behaviour is not limited to a specific subgroup of firms, the author stresses that firms holding patent-backed debt performed 49 percent of public-sector R&D and 41 percent of patenting activity in the US since 2003. The study considers only pledges that are explicitly stated in respective loan contracts. Similar to asset-based lending with tangible property, debt is thereby secured by specific assets (i.e. patents), whose liquidation value is the key determinant of creditors' payoffs in bankruptcy.

However, the indirect use of patents in loan contracts is likely even more important. Lian and Ma (2019) find that asset-based-lending only constitutes about 20 percent of non-financial corporate debt. In contrast, the remaining 80 percent of corporate debt is actually based on cash flow-based lending. This debt is not tied to any specific asset, but rather based on future cash-flows and, hence, informational content on the company. Those instances do not require any type of (physical) assets. Instead, firms borrow today by promising future cash flows. While it is well

[6] For example, patents usually protect novel (i.e. unprecedented) innovative steps, which impedes comparisons with prior art by definition. Moreover, uncertainty about patents' future income streams hinders precise evaluation. As such, the value distribution of patents is highly skewed towards mostly low-value, low-impact patents, while few other patents carry substantial value (Gambardella *et al.* 2007).

known that information asymmetries can cause credit rationing (see e.g. Stiglitz and Weiss 1981, Holmström and Tirole 1997), patents can thus relax those borrowing constraints by informing investors about future performance.

Patents generate cash flows in multiple ways. First, the application of process related patents may lead to cost savings. Second, product related patents might account for new or higher quality products, which allows firms to appropriate increasing returns both along the intensive (increase of price margins) or the extensive margin (expansion of sales). Third, due to its purpose of granting temporary monopoly rights to the patent holder, patents fend off competitors by constituting entry barriers. Fourth, patenting allows for licensing, which directly generates streams of royalty payments. At the same time, of course, every patent that a firm possesses marks a relief from opportunity costs, i.e. potential savings from license fees that would incur to the firm if it did not hold the patent.

Empirical evidence supports these considerations. Farre-Mensa *et al.* (2017) exploit the quasi-random assignment of patent applications to different patent officers with different propensities to grant applications. This allows causal inferences on the effect of a patent grant. The authors show that obtaining a patent increases sales growth by, on average, about 80 percent relative to control firms.

Finally, by filing and maintaining patents a firm provides valuable information to potential investors. In accordance with Spence (2002), patents are a signal of productivity. Creation of patents requires effort and a minimum of technological quality and novelty and informs potential lenders about the quality and value of a firm's inventive capacity (Conti *et al.* 2013). Empirical studies provide supportive evidence of this. Haeussler *et al.* (2014) find a positive impact of information gathered in the patenting process on financing decisions of venture capitalists. Similarly, Saidi and Zaldokas (2017) show that information disclosure as a means of signaling helps patenting firms to lower their costs of debt. Hence, signaling values associated to patents further allow firms to attract debt financing in an implicit manner.

2.2 Hypotheses

2.2.1 Patents and leverage

Our first hypothesis directly relates to the fact that both explicit and implicit use of patenting in the context of loan contracts help support external debt financing. Just like other forms of assets, patenting should positively relate to leverage by increasing firms debt capacity.

To obtain a properly testable hypothesis, however, we have to specify the relevant dimensions of patenting in the context of firms' borrowing activities. Most analyses use patent filings as an indicator for firms' patenting activities. However, a sizable fraction of all newly filed patents are actually very short-lived. In these cases, either protection never becomes valid or expires soon after filing. As such, in the European Union during the 2000s, the average share of granted patent filings is around 50 percent (see Figure A1 in Appendix C). Furthermore, even if the patent is granted only in one out of five cases is it active until the maximum of 20 years of protection is reached (IP5 2018). Approximating firms' patenting activity by (granted) filings thus overestimates the actual number of patents a firm possesses, particularly several years after the initial application. Intuitively, filing a successful patent is a necessary but not sufficient condition to effectively alter firms' debt capacity. Instead, only if this patent is still actively held, it should be a meaningful determinant for firm leverage. Hence, we first hypothesize that:

H1: *The number of actively held patents reduces the agency costs of the lender and thereby leads to a higher debt to asset ratios of firms in equilibrium.*

2.2.2 Patent value

We also propose that the potential of attracting external debt significantly varies depending on the properties of the patent portfolio itself. In accordance with Haeussler *et al.* (2014), the commercial value of firms' patents is most important from an investor perspective. Patent stock size and market value appear complementarily important for their commercial value just like with tangible property. Hence, not all patents have the potential to increase firms' debt capacity. More specifically, patents on the lower end of the value distribution are less likely to meet demand in the market as compared to those in the right tail. For example, it appears reasonable to assume that a large amount of low value patents is unlikely to attract investors, who are interested in (reliable) future cash flows. Thus, we hypothesize that agency problems can only be (partly) solved by providing an economic meaningful number *and* value of assets:

H2: *The overall patent portfolio value is the main driver for reducing lenders' agency costs and thus a higher portfolio value leads to a higher firm debt to asset ratio in equilibrium.*

2.2.3 Patent characteristics: specific vs. general

The underlying characteristics of the portfolio play a crucial role for firms' ability to secure loan contracts with patents. As such, the commercial value of a technology is not just a function of size and market value of the patent stock. Instead, it appears likely that qualitative dimensions are likewise important factors.

For instance, patents referring to a broader spectrum of technology classes should deliver higher anticipated liquidation value due to a higher number of potential (subsequent) users. The breadth of a patent determines the boundaries of the exclusive rights of a patent owner and therefore aspects that can be legally protected and enforced (Zuniga *et al.* 2009). Gambardella *et al.* (2007) argue that a broader portfolio increases patent portfolios' revenue inflow. The authors argue that greater vertical specialization of general-purpose technologies leads to more distant users, lower competition and higher demand for the use of the patented invention. Hence, we consider generally applicable inventions to be more likely to attract external debt. We therefore conclude our third hypothesis:

H3: *Patent portfolios that cover a broader technology space are more likely to have an effect on debt to asset ratios of the respective firms.*

2.2.4 Industry's propensity to patent

In addition to these considerations, we also expect that the effects of patenting on leverage depend on factors that lie outside the scope of patent portfolio characteristics. We propose that the advantage of patents as quantifiable assets should increase with an industry's propensity to patent. In industries where patents are a common business strategy, the information content can be more directly related to firms' future economic prospects. The arguments of the aforementioned hypotheses assume that information on quantity and quality of firms' patent portfolios are reliably known. If patenting was not a common business practice in the business environment of the firm, it is more difficult to evaluate the additional benefits arising from patents.

In this context, we suggest that industries associated with high patenting propensities are manufacturing sectors, i.e. tech-oriented industries.[7] According to the European Patent Convention (EPC 1973, Art. 52(1)), one of the four basic requirements for the patentability of an invention is that the invention has to have a "technical character". Due to the technical nature of many products, manufacturing sectors can be expected to have an obvious tendency to patent. In contrast, in knowledge intensive or service oriented sectors seeking protection via other related property rights seems be more appropriate.

- Insert Table 1 here -

Table 1 displays patenting and lending activities by tech- versus non-tech firms in our sample. On average, tech-firms file more patents, maintain their patents at a higher number of jurisdictions, and more frequently have a large patent portfolio. Notably, they have lower leverage but a higher dependence on external funding as compared to non-tech firms. Therefore, patenting should attract debt finance particularly in sectors in which it is a well-established business strategy. We thus formulate the third hypothesis as:

H4: *Effects of patent portfolios on firms' debt to asset ratios predominantly applies in industries with a high propensity to patent, i.e. tech sectors.*

2.2.5 Strength of patent protection

As a final proposition, we suggest that the market environment is an important determinant for inventors to appropriate returns on their IPR. Particularly, the level as well as the reliable enforcement of patent protection affects the probability of a patent to be used as security in a loan contract, as it alters their fundamental value of patents. Patents grant their owners the temporary right to the exclusive use of a certain inventive step or technology. Because patents are a legal

[7] We follow the Eurostat (2018) definition of tech versus non-tech firms, see Table A1 (Appendix B).

construct, their value strongly depends upon the appropriability of the right to exclude others. For example, Gambardella *et al.* (2007) claim that free riding on other firms' invention becomes more difficult, the more thorough patent protection is. Thus, enhanced protection and enforcement makes it more difficult for rivals to invent around a patent.

This is also reflected in the circumstance that European patents have to be activated in each EPC country individually. The value of a patent is essentially zero in a country where the patent is not valid and the exclusive right to appropriate an invention is therefore not given. In a similar vein, the value is close to zero if the patent cannot be properly enforced despite being eligible for protection from a legal stance. Accordingly, the value of a patent is tied to the potential to make use of the underlying right.

Empirical literature thoroughly documents this relation. In a general manner, Rampini and Viswanathan (2013) show that limited enforcement determines collateral constraints. More directly, Aghion *et al.* (2015) show that competition induces firms to increase their R&D intensity only when patent protection is strong. Similarly, Arora and Ceccagnoli (2006) suggest that more effective patents protection enhances the propensity to license patents in the absence of complementary assets. Finally, Mann (2018) shows that an exogenous strengthening in creditor rights induces firms to increase R&D expenditures. Given these aspects, better patent protection and enforcement should facilitate attracting external debt via patents stocks. The final hypothesis therefore reads as follows:

> **H5:** *Stronger patent protection and enforcement increases the likelihood that large and valuable patent stocks to have an effect on firms's debt to asset ratios.*

3 Data and empirical approach

3.1 Data sets and descriptive statistics

Combining information from two data sets, we construct a sample of mostly small and medium-sized private European firms covering the years 2000-2012. We obtain firm-level financial information from historical vintages of the Amadeus database, provided by Bureau van Dijk. and merge them to patent information from the PATSTAT database, which covers the universe of patent applications at EPO. We exclude implausible observations, such as data points with zero or negative total assets, firms that could not be categorized in industry-classes, financial firms, and those active in public sectors. Moreover, our main sample only includes firms with at least one active patent at a given year of the sample period filed at the EPO.[8]

The final data set contains 51,719 observations (representing 5,680 firms). In total, information on 96,800 individual patents are gathered and aggregated on a firm-year level. To avoid survivorship

[8] The focus on EPO filings is due to the transparent documentation of annual renewal payments. National patent offices use various different indicators on these payments. Notably, EPO filings are associated with higher patent quality, larger firm size and certain industry agglomerations (Harhoff *et al.* 2018). However, these confounds should not affect our results systematically, because we conduct within-group comparisons and control for time-invariant heterogeneity among firms with fixed effects.

bias, we allow firms to enter and leave the database. Firms appear on average 9.1 times throughout the sample period of 13 years. Our sample covers ten different European countries (Belgium, Denmark, Finland, France, Germany, Ireland, Italy, the Netherlands, Sweden, and the United Kingdom).[9]

- Insert Table 2 here -

Table 2 provides summary statistics on financial and patenting variables of sample firms. To avoid biased estimates from outliers, we truncate variables at the 1st and 99th percentile. Sample firms are on average 27 years old (with a median age of 18 years) and are privately-held (only 5.3 percent of the original sample are publicly listed). Most importantly, descriptive statistics show that patenting activities vary strongly across firms. While the average firm obtains an average patent portfolio size of about than five patents, the maximum portfolio size is 2,684 patents. Similarly, while on average patents are renewed seven times and valid in nine jurisdictions, some patents are never renewed or only valid in one jurisdiction.

Table 3 displays the distribution of firms across two-digit NACE Rev.2 main categories. The majority of firms (56 percent) are in the manufacturing sectors. In line with our hypothesis 4 and first descriptive statistics on patenting activities (Table 1), this distribution mirrors the high patenting propensity of tech-firms as compared to non-tech sectors.

- Insert Table 3 here -

Table 4 therefore compares (high-) tech and non-tech firms according to their main firm characteristics. There are distinct differences between these subgroups. First, regarding their financing situation, tech-firms have lower leverage and cash holdings as compared to non-tech firms, while facing higher interest burden, i.e. interest expenses as a fraction of outstanding debt. Second, tech firms exhibit higher growth and profitability rates and are smaller according to different size measures, such as employee headcount, tangible-, and fixed assets. Third, tech firms are more active patentees, not only in terms of filings but also regarding the share of firms having large patent stocks. These differences in patenting are particularly pronounced for high-tech firms. Combined, these aspects confirm that technology oriented firms yield higher rates of inventive output and growth, but are at the same time more restricted on their funding resources.

- Insert Table 4 here -

[9] Our original sample includes all EU-15 member states at the onset of the sample period in 2000. However, five countries had to be dropped due to inconsistent data availability (Austria, Greece, Portugal, and Spain) and because of validity concerns (Luxembourg contains mainly financial firms). For an overview on the distribution of observations among countries, see Table A2 (Appendix B). With the exception of Italy, our sample resembles the true distribution among European countries fairly well, including countries according to their proportional share of the total population.

3.2 Measurement strategy

To address our research questions properly, the quantification of firms patenting activities has to incorporate certain key features. First, it has to reflect relevant dimensions of firms' inventive output. Second, it needs to carry informative value for potential investors, i.e. be a good proxy for future cash flows. Third, we need to be able to precisely track these two characteristics over an extended period of time, in a way that accounts for variation across time and firms.

In our empirical estimations, we therefore consider the actual size and value of firms' *patent portfolios*, i.e. all active patents of a firm at a given time. This includes qualitative patenting features that relate to the market value of firms' patents and captures the notion that both the amount and the value of assets determine their potential of affecting firms' debt capacity. We follow the literature (e.g. de Rassenfosse and Jaffe 2018) in approximating the market value of a patent by the number of jurisdictions at which patents are filed, i.e. the so-called family size of a patent.

Incorporating these two dimensions, we define our main patent measure therefore as follows: $patent\ stock_{it} = act.\ patents_{it} \times avg.\ value_{it}$, where $act.\ patents_{it}$ is the number of active patents of firm i at time t and $avg.\ value_{it}$ equals the year-specific average number of jurisdictions all patents in a given portfolio (i.e. $act.\ patents_{it}$) are active.[10] Because of strong industry and cyclical heterogeneity of patenting activities, we normalize patent-specific variables on an industry-year basis.[11] This approach also mitigates concerns regarding strategic patenting behaviour, which is correlated with industry- and time-specific characteristics of firms (Lerner and Seru 2017). In the spirit of our hypothesis 2, combining both quantitative and qualitative features in the patent measure suggests that asset size and value equally important for attracting debt.

Figure 1 drafts the correlation between the size of firms' patent portfolio and their leverage ratios in a binned scatterplot that distinguishes among firms with an above and below median patent portfolio values. Regarding the linear fit suggests a positive relationship between the patents and leverage for high value portfolios. In contrast, the size of low value portfolios does not relate to leverage ratios. Similarly, recasting the binned scatterplot with patent fillings instead of the actual patent stock on the y-axis suggests that filings do not explain heterogeneity in leverage ratios either (see Figure A3 in Appendix C). Hence, these graphical illustrations support our proposition to regard the size as well as the value of actively held patents when analysing the effect of patent portfolios on firms' debt capacity.

- Insert Figure 1 here -

A distinct feature about the European patent system provides the core of our measurement strategy. To fully utilize the information on patent stock size and value, we have to track the two

[10] Figure A2 (Appendix C) displays the evolution of the two dimensions across sample years. Considering the two dimensions provides a useful source of variation in our dataset.

[11] We calculate normalized values of any patent variable p for firm i in period t by: $p_{it}^{norm.} = p_{it}/Q99\,p_{st}$, with $Q99\,p_{st}$ being the 99$^{\text{th}}$ percentile value of variable p in sector s at time t. For robustness, we repeat our main findings using non-normalized variable specifications.

dimensions over the entire lifespan of each individual patent. For this purpose, the EPO renewal schedule enables a unique way of measuring firms patent activities. Here, but unlike in other jurisdictions, renewal fees have to be paid in every Contracting State[12] of the European Patent Convention (EPC) *and* in every year for which the protection pertains, beginning the third year after initial patent filing. Thus, patent protection can be maintained independently across these national patent offices, such that patentees choose where and how long to maintain protection individually. Our data contains information on whether and where a firm has actually made a renewal payment on a yearly basis. According to the EPO (2018), these renewal fees are a direct indicator for the validity of a patent and enable us to quantify the actual size of firms' patent portfolios even years after initial filings.

This institutional setup is pivotal for our analysis. Maintenance systems notably differ from country to country. For instance, the United States Patent and Trademark Office (USPTO) does not collect annual renewal fees but instead collects payments only after 3.5, 7.5, and 11.5 years, respectively. Hence, in this case, validation fees are not able to explain whether a patent is indeed active.

To illustrate the significance of different fee schedules in determining the lifespan of a patent, Figure 2 compares the validation rates of patents filed at EPO and USPTO. Because important inventions may not be important in the future anymore, these rates mirror declining values of patented inventions as technological progress evolves over time. However, only the annual renewal schedule at EPO resembles this notion. The fraction of patents held for an extended time is much larger at the USPTO compared to grants from EPO. While 50 percent of EPO patents are held seven years after application, 50 percent of USPTO patents are maintained for about 17 years.

- Insert Figure 2 here -

3.3 Baseline specification

In our model specifications, we follow Rajan and Zingales (1995) and consider firms' leverage to equal total (long-term) debt over total capital as dependent variables. Total capital thereby equals the sum of total equity plus total debt of a firm within a given year. Long-term debt is defined as loans and liabilities with a maturity of more than one year. In additional checks we alter the definition of leverage to demonstrate the robustness of our results. As main explanatory variables, we use the well-established firm characteristics that determine their debt-equity choices: i) size, ii) profitability, iii) tangible collateral, and iv) operating risk. Table 5 defines these capital structure determinants. Following Bertrand *et al.* (2004), standard errors are heteroscedasticity-consistent and clustered at the firm level. Hence, Equation (1) specifies the baseline model:

[12] As of March 2019, Contracting States are Albania, Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Liechtenstein, Lithuania, Luxembourg, Malta, Monaco, the Netherlands, North Macedonia, Norway, Poland, Portugal, Romania, San Marino, Serbia, Slovakia, Slovenia, Spain, Sweden, Switzerland, Turkey, and the United Kingdom.

$$Leverage_{it} = \theta_i + \gamma_{ct} + \beta_1 \, Patent_{it-1} + \beta_2 \, CS_{it} + \varepsilon_{it} \quad , \tag{1}$$

where θ_i and γ_{ct} are firm- and country-year-fixed effects. CS_{it} is a vector of capital structure determinants as well as a one year lagged value of the dependent variable which accounts for serial correlation in the panel structure of our data. $Leverage_{it}$ measures firm i's debt ratio at the end of period t. $Patent_{it-1}$ is the regressor of interest and measures the patent portfolio of firm i at the beginning of the period. Hence, β_1 is the coefficient of interest.

- Insert Table 5 here -

3.4 Identification strategy

3.4.1 Institutional background: the Enforcement Directive

In the baseline specification, Equation (1), we mitigate reverse causality concerns to a certain extent by using the lagged level of the patent portfolio measures. Still, this approach controls for the direction of causality only imperfectly. We therefore exploit the EU Directive 2004/48/EC (Enforcement Directive) as an identifying event affecting the value of patent portfolios. We expect strengthened enforcement to enhance usage of respective patent stocks (i.e. increasing future expected cash flows) and thereby increasing firms' debt capacity. Everything else equal, exogenous variation in patent value should therefore lead to changes in firms' leverage which can be interpreted causally.

The general objective of the Enforcement Directive is to approximate legislative systems in EU member states so as to ensure high, equivalent and homogenous level of protection of intellectual property rights. In this context, the Directive sets out several measures, procedures and remedies, which are required to ensure the enforcement of respective rights. More specifically, the Directive aims at "*creating an environment conducive to innovation and investment*" (Art. 1). Overall, the Enforcement Directive can be interpreted as a strengthening of the reliability and effectiveness of IPR through improving civil enforcement in a harmonized cross-country setting. Table A3 (Appendix B) summarizes the Articles of the Directive.

In line with this, implementing the Enforcement Directive is relevant both for firms as well as potential investors. First, enhanced protection against copying should increase the fundamental value of a patented invention from a firm perspective. Because inventions are commonly non-rival, a more thorough enforcement helps firms to prevent unlawful use of their technology, ultimately making the use of IPR a more reliable business strategy. Second, also from an investor's perspective, patents become a more valuable asset (see also Hypothesis 5). Improved enforcement decreases the level of uncertainty regarding potential appropriation of returns. Moreover, as firms' propensity to patent should increases, the credibility of using patents as a quality signal also increases. Being an important signaling instrument, the information content embodied in firms' patenting activities becomes more reliable.

A comprehensive evaluation study ascertains that the Directive is an effective tool on a general and conceptual level improving enforcement of IPR (EU 2017). According to Fleissner (2009), the legislative piece makes IPR more resilient against illegal copying and thereby strengthens its role in general. In a multi-country setup, such as in our analysis, these aspects are particularly crucial. Despite international agreements (e.g. the TRIPS agreement), there is no global patent system. In fact, countries have the ability to individually determine major aspects of their national IP – and patent – systems. This fragmented nature of patent protection, impedes consistent enforcement across jurisdictions (Hall and Helmers 2018). In line with previous considerations, this is detrimental for the value of patents as a legal construct that defines the borders of firms inventive activities. On the contrary, attempts to harmonize respective IP rights should have a positive impact on the value of patenting rights (Mann 2018).

In essence, based on this evidence we expect the Enforcement Directive to improve IPR enforcement throughout the EU and thereby translate to a higher market value of respective intellectual property. The staggered implementation across EU member states thus constitutes a well-suited setting to study the impact of increased market value of firms' patent stock on leverage.

3.4.2 Econometric implementation

Our empirical strategy aims at mitigating endogeneity concerns in several ways. Unlike other forms of EU law, the timing of EU Directives' implementation commonly varies considerably across member states (Kalemli-Özcan *et al.* 2013). For example, Denmark, Italy, and the United Kingdom implemented the Directive already in April 2006, whereas Sweden passed the amendments through domestic legislation only three years later (see Table A4, Appendix B). This sequential implementation is unlikely to pick up market responses, because variation in the timing is mostly attributed to differences in national legislative procedures (compare with Christensen *et al.* 2016). Additionally, implementation decisions are made on a supra-national level, whereas individual firms' actions should be only related to specific country initiatives (Schnabel and Seckinger 2019). Finally, the Directive addresses issues of IPR in general, while our explanatory variables capture only one specific dimension, patenting. It appears implausible that countries adapt their legal framework of an entire group of IPRs just to target one specific dimension.

These factors enable estimation of the causal effect of increases in the market value of firms' patent portfolio on their capital structure by employing a difference-in-difference methodology. Equivalent to the baseline setup, the panel structure of the data allows us to control for unobserved heterogeneity across firms and the cyclicality of lending patterns by including fixed effects. Equation (2) captures the augmented baseline specification:

$$Leverage_{it} = \psi_i + \delta_{ct} + \alpha_1(Patent_{it-1} \times Post_{ct}) + \alpha_2 Patent_{it-1} + \alpha_3 Post_{ct} + \alpha_4 CS_{it} + u_{it} \ , \quad (2)$$

where ψ_i and δ_{ct} are firm- and country-year fixed effects. CS_{it} is a vector of the capital structure determinants and $Leverage_{it}$ measures the long-term debt ratio of firm i at time t. $Patent_{it-1}$ measures the size and market value of firm i's patent stock at the period $t-1$. All remaining variables are specified in Equation (1). $Post_{ct}$ is a dummy variable equal to one if the Enforcement Directive applies in country c at time $t-1$ or zero otherwise. The coefficient of interest, α_1, captures the average treatment effect, i.e. the effect of strengthened IPR on financial leverage.

In our setup all firms are treated, because the Directive does not only apply for certain subgroups but rather affects all firms within the respective jurisdiction. Nevertheless, for strengthening identification, we do not only limit our analysis to the utilization of cross-country variation in the implementation dates. Instead, we additionally exploit heterogeneity in the different degrees to which firms are affected within countries. Because firms from tech sectors are associated with a more pronounced propensity to patent, effects of the Directive can be expected to be significantly stronger for this subset of firms. Hence, we utilize this heterogeneity in firms' patenting propensity as final step of our identification strategy.

4 Empirical results

4.1 Baseline results – Portfolio size and value

Table 6 displays the estimates on the baseline specification as defined in Equation (1). We obtain consistent and statistically significant coefficients across all specifications regarding the standard capital structure determinants (Column I). Specifically, estimates show a positive correlation coefficient for firm size and tangibility measures. In contrast, for profitability and operating risk (i.e. cash holdings) estimations relate to firms' debt-to-equity choice negatively. These outcomes are well in line with standard results from the literature of capital structure determinants. Hence, our modeling approach is able to replicate previous findings consistently, which provides first ground for the validity of our sampling. On top of this and most importantly, our coefficient of interest (*Patent stock*) is positive, statistically significant at the five percent level and sizable in economic terms (Column II). One standard deviation increase in the patent measure increases the average firm's financial leverage by 8.6 percent. These results support our hypothesis 1.

In Column III , we change the patenting measure to the simple filing measure. The correlation coefficient remains positive but become much smaller and is no longer statistically significant. Combined with our first descriptive evidence, this shows that filings do not have strong explanatory power for firms' debt capacity.

In Columns IV-VI, we change the regressor to a measure of the patent stock, which exclusively captures the number of active patents in the patent stock. As compared to the patent stock measure incorporating the value relevant dimension (21.283), the effect of this regressor is much smaller (9.606). This confirms that similar to tangible assets the market value of patent portfolios is important in explaining its ability to attract debt financing. Splitting the sample according to the high and low portfolio values further validates this finding (Columns V and VI). Comparing the size and the statistical significance of the coefficients suggests that results are driven by the high value patent portfolios. Results therefore support the view that larger patent portfolio can be associated with a higher leverage ratio *conditional* on high market value of the respective portfolio, which is in line with our second hypothesis.

- Insert Table 6 here -

Interestingly, with one particular exception the remaining capital structure determinants remain similar in magnitude in these split samples. Only the coefficient on asset tangibility is significantly different. For the low quality patent portfolios, tangible assets are much more important in explaining firms' debt capacity. Hence, tangible and intangible assets (i.e. patents) appear to be substitutes.

To show that results are not driven by the distinct model specifications, we re-estimate regressions using alternative definitions of the dependent variable and our main regressor (see Tables A5 and A6 in Appendix B). These adjustments do not affect our results. Further, we test the appropriability of the specified lag level of the patent measure. When repeating the baseline regressions using different leads and lags of our main regressor, we do not find such anticipatory effects, whereas estimates appear most sizable for the one-year lagged patent stock measure (see Table A7 in Appendix B).

4.2 Baseline extensions – Generality and industry characteristics

Following our hypothesis 3, we next test whether patent portfolios covering a broader technology space have a more pronounced effect on firms' debt capacity. We measure the breadth of firms' patent portfolios by the so-called originality index (Trajtenberg *et al.* 1997, Hall *et al.* 2001). This index captures the technological range to which a patent relates and the nature of the research on which it is based. All patents contain a set of citations, referring to previous technology, science, or literature. The technological areas (IPC 4 digit classes) of these backward citations are classified and define the scope - or the number of different technology classes - to which each patent refers. High numbers resemble broader patents (vice versa).[13] In the following, we define portfolios referring to one single technology class as $specific$ (resembling 35.2 percent of all portfolios), whereas all others are generally defined as $broad$.

- Insert Table 7 here -

Table 7 contains estimates for our baseline setup augmented with the originality index to assess whether broader or more specific patent (portfolios) affect firms debt capacity. First, specific

[13]We utilize the measure in the sense of a Herfindahl-index based on the number of different technology classes respective patents refer to: $originality_it = \sum_j^{n_i} bwd_{ij}^2$, where bwd_ij is the percentage of backward citations made by patent i that belong to patent class j, out of n_i patent classes. Hence, if a patent cites patents belonging to a wide range of technological fields, the measure is low. If most (all) citations refer to few different fields, it will be close (respectively equal) to one. For estimations, we take the average originality value of all patents of firm i in year t.

patent portfolios do not account for the positive effect of patent portfolios on leverage. While coefficients on all specifications of broad patents are positive and significant, the coefficient on the subsample of specific patent portfolios is negative and insignificant. Second, results suggest that the magnitude of the effect increases with the degree of originality, that is with the number of different technology classes the patent portfolio encompasses on average. We split the sample according to the patent portfolios that lie above the 66$^{\text{th}}$,- 33$^{\text{rd}}$-, and 25$^{\text{th}}$-percentile of the originality distribution, respectively. The size of the coefficient increases for higher levels of breadth: from 17.362 to 30.390 to 58.665. Results of this exercise support hypothesis 3.

As a second extension, we assess whether a given firms industrial sector leads to differential effects. In a set of repeated regression estimations that are displayed in Table 8, we provide evidence for the hypothesis that the effect of patenting on leverage depends on the industry's propensity to patent. In Columns I and II, we split the full sample according to whether firms belong to a tech sector or not. For tech firms, the coefficient of interest is very large and statistically significant across specifications. In contrast, the size of the coefficient of interest is negligible and statistically not different from zero in the case of non-tech firms.

The last two columns display regressions on all firms, including the regressor of interest: patent stock. Column IV includes the interaction term of the patent measure with a binary indicator equal to one for firms belonging to the tech-sector. This confirms that the aforementioned effects are more pronounced for firms from tech sectors (Column IV). The coefficient of the interaction term of the industry affiliation is large and of highest statistical significance providing evidence that effects are stronger for firms that are located in industries where patenting is a common business strategy.

Additionally, despite small variation regarding the level of statistical significance, the standard capital structure determinants do not vary strongly across these industries. This suggests that variation on patent variables is not driven by specific differences among these subsamples. Our findings therefore confirm observations from previous literature and provide further ground for the validity of our overall results. Hence, we can confirm hypothesis 4 stating that the positive effect of patenting on firms' debt capacity predominantly applies to firms located in industries with high patenting propensity.[14]

- Insert Table 8 here -

Furthermore, we combine the analysis of patent- and industry characteristics. While the effect of the patent portfolio is heterogeneous across different degrees of patent breadth, the originality index itself is equally distributed among firms in different industry sectors. Descriptive statistics from Table 4 show that mean originality index values for non-tech (0.780), medium- and low-tech (0.782), and high tech sectors (0.783) are not statistically significantly different among sectors. Our results from Table 8 refer exclusively to firms in tech-sectors. We thus repeat the exercise for non-tech firms. Because of the different degree in specificity of the patent portfolio, it might well

[14]In undisplayed output tables, we further test the robustness of these results. Our estimates are robust to different model specifications analogously to those conducted for the baseline regressions displayed in Table 6.

be the case that very broad patent portfolios have an effect even for firms located in sectors with low propensity to patent.

Results summarized in Table A8 (Appendix B), however, do not provide any evidence of this. Even though the correlation coefficients also become larger for the sample of non-tech firms, none of the results is statistically different from zero. While first results provide supportive evidence on our hypothesis 3 stating that more general patent portfolios have a stronger positive effect on firms' debt capacity, these findings do not hold for non-tech firms. In turn, it appears that patent characteristics are important for determining firms' debt capacity, but only conditional on the industry affiliation.

4.3 Identification – The Enforcement Directive

The next part of the empirical analysis addresses endogeneity concerns and tests our hypothesis 5 simultaneously. We exploit the staggered introduction of the Enforcement Directive marking a positive exogenous shift in the value of firms' patent stock. For appropirate identification, we differentiate among tech and non-tech firms. Figure 3 summarizes those findings graphically and illustrates both an overall increased positive effect of firms' patent stock value on leverage as well as a disproportionate effect for tech firms.

- Insert Figure 3 here -

To assess the effects in more detail, Table 9 shows estimate on a set of regressions as specified in Equation (2). The key addition to the baseline specification is a country-specific indicator variable on whether the Enforcement Directive passed domestic legislation. The respective positive and highly significant coefficients across specifications imply that leverage is generally higher for all firms in the post-implementation period independent from the patenting stock. Moreover, in Column III the *post* indicator is interacted with the patent stock measure. The corresponding coefficient is sizable and statistically significant at the one percent level. At the same time, the coefficient on the patent variable becomes small and statistically insignificant. This indicates that the directive had a positive effect on the use of patents to enhance firms' debt capacity.

- Insert Table 9 here -

To mitigate endogeneity concerns, we utilize heterogeneity in the treatment effect arising from the relatively high patenting propensity in tech sectors. In Column IV, we therefore additionally multiply the interaction term with the indicator variable on whether a firm belongs to the tech sector or not. This triple interaction term captures most of the patent stock variable's effect. The coefficient is large (19.020), whereas the coefficient of the interaction term of *patent stock* and *post* becomes much smaller (8.212). Moreover, the coefficient of the single *patent* variable (3.140) remains small and statistically not different from zero. The impact is quite sizable in economic terms. After the implementation of the Enforcement Directive one standard deviation increase in the patent stock variable increases the leverage ratio of the median (mean) tech firm by 18.4 percent (7.7 percent) - or 1.3 percentage points.

In a final step, we re-estimate the regressions on tech and non-tech firm subsamples, which allows us to estimate heterogeneous treatment effects without using a triple interaction term. Columns V and VI display results for respective subgroups of firms. In the tech-group subsample, the coefficient of the interaction term of *patent stock* and *post* is large (24.785) and significant at the one percent level. In contrast, for the non-tech group subsample the respective coefficient is relatively small (8.323).

All these observations provide strong evidence confirming hypothesis 5. Hence, an exogenous increase in the value of first patent stock translates to an increase in firms' financial leverage. Notably, this result is strongest for firms we expected to be affected by such a treatment — those belonging to the tech sector. We thereby are able to causally estimate the effect of patent portfolio value on firms' leverage.

4.4 Robustness section – Validation of empirical results

4.4.1 Anticipatory effects and parallel trends

In the following subsection, we test for the robustness of our baseline findings. The key identifying assumption in our setup is that leverage trends are the same for both tech and non-tech firms in the absence of treatment. Thus, firms have to follow a common path, before the treatment becomes effective, while differing afterwards. This is particularly crucial because tech and non-tech firms are systematically different along several covariates, such as growth, size, and use of external funding. We therefore test whether parallel trends between these firms exist using techniques in the spirit of Granger (1969). More specifically, we estimate a regression in which country-specific time dummies for each year preceding (and following) the treatment are interacted with the indicator whether a firm belongs to the tech sector or not.

If firms move along similar paths, estimates on these interactions should not be statistically significant from zero during the pre-treatment period. Figure 4 graphically displays the correlation coefficients and the corresponding 95 percent confidence intervals of the interactions using the regression setup from Equation (1), which controls for other capital structure determinants, country-year fixed-effects and the lagged dependent variable. Considering the coefficient plot, in none of the years preceding the implementation of the Enforcement Directive, correlation coefficients are statistically different from zero. After controlling for relevant firm characteristics, both tech and non-tech firms seem to move along parallel trends regarding their leverage decisions during the pre-treatment period.

- Insert Figure 4 here -

In addition to this, Table A9 (Appendix B) provides further tests on the prevalence of anticipatory effects by repeating the underlying regression of Figure 4 according to different model specifications. None of the estimates points towards a statistically significant different trend between high tech and non-tech firms' leverage decisions before the treatment. Thus, we do not find evidence that leads us to reject the identifying assumption of parallel trends between the tech and the non-tech group.

For precautionary reasons, we test for the necessary condition of the parallel trend assumption in an additional way. Estimates displayed in Table A10 (Appendix B) contain a time trend variable ($trend$), which is a simple running number of the sample years as well as an interaction of the treatment dummy variable with this time trend. If the regression coefficient of this interaction term is statistically not different from zero, parallel trends during the pre-treatment period between subgroups can be reasonably expected (Angrist and Pischke 2008). Confirming the above findings, the coefficients of respective interaction terms are statistically insignificant.

4.4.2 Lag structure

In a next step, we analyze the lag structure of the treatment effect, that is the detailed effects in the years following the implementation of the Enforcement Directive. Figure 5 first presents graphical results of this analysis by plotting the interaction of year dummies with the patent stock variable both for the tech and non-tech groups. It captures the effect of firms' patent stock on leverage relative to the implementation year. Reconfirming our previous results, estimates on correlation coefficients in the pre-treatment period are low and are statistically insignificant. This is true for firms from all sectors. Moreover, in the post-treatment phase, we observe a different picture. On the one hand, all estimates on tech firms' correlation coefficients are positive, increasing over time and statistically significant at the one percent level. In contrast, for non-tech firms estimates remain rather unchanged. Thus, the paths clearly diverge after the treatment occurs.

- Insert Figures 5 here -

Further, we investigate the lag structure of the Enforcement Directive's effect on leverage by means of repeated regression analyses on different subsamples. Unlike in the graphical illustration this exercise focuses exclusively on the post-treatment period. Results displayed in Table A11 (Appendix B) illustrates the time structure of the treatment impact and mirrors the graphical results from above. On the one hand the impact becomes more sizable over time: For firms from the tech-sectors it increases almost threefold from 13.168 for the first lag to 35.743 for the fifth lag. Between the fourth and the sixth lag, the effect remains at a relatively similar magnitude (compare with Column I). On the other hand, for non-tech firms coefficients are not different from zero (-0.392) for the first lag, increase up to the fifth lag (9.352), but remain statistically not different from zero throughout all lags (Column II). These results are stable across econometric model specifications. Overall, results show that full effects of the exogenous shock on firms' debt-ratios unfolds over time but remains stable thereafter (i.e. four years). This illustrates that the impact of legal amendments diffuse gradually, especially in the case of harmonization processes, which are dependent on mutual implementation of the respective change in the legal framework.

4.4.3 Public versus private firms

Next, we investigate whether results are confounded by publicly listed firms. Large public firms are oftentimes responsible for a large fraction of overall patenting activities.[15] As such, in our sample, these firms hold on average significantly more patents (7.7 patents) as compared to private firms (4.8 patents). Moreover, the frequency with which quoted firms hold sizable patent portfolios (i.e. more than five patents) is almost twice as high for quoted firms (20 percent) as compared to private firms (11 percent).

In our baseline specifications, we voluntarily exclude publicly listed firms, because these firms do not consider bank debt as their main source of external funding. Additionally, public firms have a broader set of funding sources available, such as access to capital and bond markets further reduces their dependency on bank finance (Freixas and Rochet 2008).[16] Following these arguments, the use of patent stocks for enhancing listed firms' debt capacity should play only a subordinate role. We test this by re-estimating the above regressions while differentiating among private and non-listed firms. Table A12 (Appendix B) shows the results of this exercise.

As opposed to private, non-listed firms the correlation coefficients of interest do not hold across multiple specifications for publicly listed firms. First, this is true for the baseline specification (Columns I, II, IV and V): while coefficients for private firms are positive, large (9.048 and 20.920) and statistically significant, the equivalent coefficients for publicly listed firms are small (-1.529 and -1.183) and insignificant. Second, re-estimating the main specification of the Enforcement Directive setup (Columns III and VI) shows that the positive exogenous shock in patent value only translates to high leverage in the case of private firms. Thus, public firms are less relevant for explaining previous results. Notably, coefficients on the main capital structure determinants (i.e. size, profitability, tangibility, and risk) are very similar across both types of firms.

4.4.4 Announcement effect

Another possible confounding factor in our analysis is that the announcement of the Enforcement Directive itself already had an effect on firms' debt equity decision. We therefore assess whether the effect of the Enforcement Directive is already measurable by the time of its proclamation in 2004.

This test draws on the logic of a placebo test and can be considered as a falsification test. The regression equation reads analogously as before, however, we exchange the treatment variable indicating the country-varying actual implementation of the directive by the placebo indicator. This dummy variable equals one for all years starting with 2004, because the Directive was finalized

[15] According to EPO (2019), the largest European patentees were Siemens, Royal Philips, and Ericsson with 2,493, 1,617, and 1,472 patent applications at EPO in 2018. 48 out of the top-50 applicants are publicly listed corporations. Overall, these top-50 applicants are responsible for approximately 26 percent of all patent applications (or 44,996 out of 174,317) during the same year.

[16] For example, bank debt ratios for private firms are higher (18.6) than those of listed firms (15.1) in our sample.

on April 29$^{\text{th}}$, 2004, by the European Parliament and the Council. We exclude years from the regression, in which both the placebo and the true indicator equal one, because this would mix announcement and treatment effects. The interaction term of the tech sector dummy and the patent measure therefore captures whether there was already an quantifiable effect at the announcement until the actual implementation of the amendment.

Table 10 shows that across specifications, both for the full sample (Columns I-III) and for the split sample (Columns IV-V), estimates on the coefficients are statistically not different from zero. This speaks against the hypothesis that already the announcement of the Enforcement Directive has an impact on the debt-equity choice of firms. Particularly, we do not observe an impact of this artificial treatment on tech sectors, as indicated by the interaction term in Column III. Overall, the plausibility test further strengthens our results and supports the design of our empirical strategy.

- Insert Table 10 here -

4.4.5 Financial crisis, survivorship effect

As another plausibility check, we test the extent to which survivorship drives our results. Our sample time frame includes the years of the Financial Crisis following 2008. The Enforcement Directive was implemented before the crisis, though. Because we allow firms to enter and exit the database in our main regressions, a valid concern is that results are driven by the fraction of firms which survives the crisis. For instance, only about 70 percent of firms during the years 2007 until 2012.

We repeat the main regression on the effect of the directive both for firms that are always observed as well as those that drop out of the data set. If results were driven by 'surviving' firms, the size of the respective estimates should be significantly higher as compared to the estimate for the drop outs. Table A13 (Appendix B) displays the results of this test. Comparing the coefficients of the full sample with the one for the 'surviving' firms, the two coefficients are virtually the same, both in size and level of significance. Moreover, the respective coefficient for the drop outs is virtually the same (23.138) compared to survivor's coefficient (23.968). At the same time, the estimate is less precise, indicated by the corresponding drop in the level of statistical significance. This might be either owed to an actual difference between the subsets or to the much smaller sample size. Nonetheless, based on these outcomes, we cannot confirm the hypothesis that survivorship bias drives the results in our setup.

4.5 Interest burden: the mechanism behind patenting and leverage

As a final step in our empirical analysis, we examine the causal link between firms' patent portfolios and their leverage ratios. In particular, if patenting improves firms' access to finance by signaling future cash flows, this should be reflected in respective firms' cost of obtaining external funding. Both direct as well as indirect use of patenting in the context of loan contracts helps reducing borrowing costs. In this subsection, we therefore investigate whether patenting affects the interest expenses of respective firms.

Because of the structure of our data, we do not observe individual loan rates. However, we are able to measure firms' interest burden as the fraction of financial expenses (i.e. interest payments and other financial charges) over the average long-term debt held during the period. Unlike the average interest rate a firm has to pay on their debt, the interest burden measure includes all financial charges of a year. Hence, this proxy tends to overestimate the burden that arises from firms' external debt holdings. Thus, the bias should lead towards underestimating the effect of patenting on firms' interest rates. Estimates using the interest burden can therefore be regarded as a conservative approach. Overall, the measure still contains sufficient informational content to assess whether patenting affects the costs of firms to obtaining external funding.

(i) Patent portfolios and interest burden

Table 11 summarizes the main estimates on the effect of firms' patent portfolios on their leverage ratios. Intuitively, the coefficients on the standard capital structure determinants are inverted compared to the baseline setup that uses debt ratios as dependent variable. We include our measure of patent stock capturing both dimensions, size and value, as well as quantitative measures of patenting, i.e. filings and the stock size. All results are negative and statistically significant (Columns II-IV). Notable, however, the coefficient on patent stock (-0.240) is more than five times larger as compared to the coefficient on filings (-0.043), respectively twice as large compared to the stock size measure (-0.100).

- Insert Table 11 here -

To confirm the important role of the patents' market value, we split the sample according to portfolios of high and low value, respectively. The coefficient for the valuable patents is large, negative, and statistically significant at the one percent level (-0.242). In contrast, the coefficient for the low value stocks is much smaller (0.075), positive but statistically not different from zero.

These results follow our finding of the baseline regressions. It is neither the size of the patent portfolio nor the number of patent filings, which drive the effect of firms' patented output on their interest burden, per se. Foremost, it is the combination of large and valuable portfolios that is associated with lower rates. These findings are not only statistically significant but also economically. For a patenting firm to move from the median of the patent stock distribution to the 90^{th}-percentile translates, on average, to a 1 percentage point decrease in the median interest burden (12.1 percent). This resembles a 8.3 percent decrease in *overall* interest burden.

(ii) Sectoral affiliation and the impact on interest burden

Analogue to our previous findings, the patent stock should influence interest burden particularly within sectors that have a high propensity to patenting. We graphically analyse the differentiated effect among tech and non-tech firms in Figure 6. The binned scatterplot illustrates a negative relationship between patent stocks and the interest burden, controlling for several confounding variables. The slope of the linear fit, however, suggests that this relationship is stronger for firms from tech-sectors.

- Insert Figure 6 here -

In line with this, a set of regression estimates displayed in Table A14 (Appendix B) confirm this notion. Both in a sample split as well as the use of interaction terms yield equivalent findings. While coefficients are negative for all subsets of firms, they vary strongly in magnitude and level of statistical precision. For tech firms, coefficients are much larger (-0.240 compared to -0.010) and statistically significant. Similarly, interacting the patent stock variable with a binary indicator for belonging to the tech sector shows that results are driven by this subset of firms. Running a regression on the full sample gives a coefficient of interest (Column III) for the patent stock variable of -0.083. Including the interaction term, reduces this value to -0.010, while both coefficients are not statistically significant. However, for the interaction term, the coefficient of interest is much larger (-0.221) and statistically significant at the 10 percent level. Again, results are analogous to those obtained from regressions on debt ratios.

(iii) Enforcement Directive and interest burden

As a final exercise to investigate the causal link between firms' patent portfolios and their leverage ratios, we want to confirm the previous results by isolating the direction of causality. We use the same identification strategy, exploiting the staggered implementation of the Enforcement Directive across different European member states as a quasi-natural experimental setting.

- Insert Table 12 here -

Consistent with our previous application, in Table 12 we test the impact of the strengthening in the European patent system on firms' interest burden exploiting heterogeneous treatment effects with respect to the sectoral affiliation of firms. We estimate two sets of regressions to translate this into our econometric specification. First, we use a triple interaction between a post implementation, a treatment dummy, and patent stock. Second, we split the sample according to tech and non-tech firms. The effects on tech firms are statistically significant, relatively large (-0.240 and -0.172), whereas the effect on non-tech firms are insignificant and of low magnitude (0.036 and 0.006 respectively). Hence, findings on either one of these specifications indicate a significant impact of the shift in the fundamental value of firms' patent portfolio on the interest burden, given the patent portfolio is sizable and of high value.

5 Conclusion

In this paper, we show that patents increase the debt capacity of firms. Importantly, we demonstrate that these effects are causal by exploiting exogenous variation in the patent portfolio value due to the staggered implementation of a European Directive across countries. Several robustness test, such as a placebo test on the announcement date or other well-established tests on difference-in-difference strategies, confirm our findings.

We employ a unique data set, combining in-depth legal patent data (PATSTAT) with companies' balance sheet data (Amadeus) across several European countries over a time span of 12 years. The distinct structure of the European patent system allows us to track the size and value of firms' patent portfolios on an annual basis. As an initial step, we replicate common findings in empirical work on capital structure determinants. We then add our patent measures and show that indeed an increase in the respective value leads to a higher leverage ratio. To the best of our knowledge, we thereby are the first who analyze the impact of patent portfolios on capital structure decisions. We further show that it is both the size as well as the approximated market value that matter for this relationship. In contrast, only using the size or the number of patent filings underestimates the potential of patents on firms' debt capacity.

In a second step, we show that this relationship is heterogeneous across patent and firm characteristics. We provide evidence that this effect is strongest for patent portfolios covering a wide range of technology classes. In addition to this, firms are better able to secure debt if they are from the tech sector i.e. in industries with a higher propensity to patent. In a combined perspective, however, the industry effect dominates the effect arising from the generality of patents.

In a final step, we show that sizable and valuable patent stocks are effectively lowering interest rate burden and thereby enhancing the debt capacities of respective firms. We find a negative and significant effect of valuable patent portfolios on firms' interest burdens. These findings also hold in our quasi-natural experimental setup using the Enforcement Directive as a positive shift in patent value.

Our results provide valuable implications both from a governmental and a managerial perspective. First, we show that intellectual property may indeed be used to support debt financing, which is particularly important for supposedly constrained, research intensive firms. Second, a harmonized, more reliable enforcement system could facilitate the use of intangibles and IPR for attracting external funding and therefore stimulate innovation. Finally, from a managerial perspective our findings urge firms to consider IP-backed financing as a potential source of support for their business and innovation activities given an appropriate regulatory environment.

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Tables from the main part:

Table 1: Patenting and debt use across industries: tech versus non-tech firms

Variable	**Min.**	**Max.**	**Tech firms** Obs.	**Tech firms** Mean	**Non-tech firms** Obs.	**Non-tech firms** Mean	**Difference in means**
Patent filings	0	144	28,928	0.514	22,791	0.314	0.200***
Large patent stock	0	1	28,928	0.136	22,791	0.093	0.043***
Patent lifespan (years)	3	20	28,928	8.978	19,036	9.044	-0.066
Active offices (avg.)	1	37	28,928	7.888	19,036	7.436	0.452***
Debt-ratio	0	100	24,968	16.323	19,036	21.154	-4.831***
RZ index	-0.33	2.10	10,895	0.242	6,307	0.381	-0.139***

Notes: The table displays comparisons in means of tech-oriented, i.e. manufacturing, firms and non-tech firms as classified by Eurostat (2018). Patent filings refers to the number of patents filed per year, per firm. Large patent stock is an indicator variable equal to one, if the firm has more than five active patents or zero otherwise. Patent lifespan equals the number of years patents are active. Active offices is the number of countries at which patents are maintained. Debt ratio is long-term debt over assets ratio (in percent). The RZ index is measured by $(Capex_{it} - CF_{it})/CF_{it}$, with $Capex_{it}$ being the total of fixed assets expenditures and CF_{it} the cash flow of firm i in period t. Lower values reflect higher dependence on external funding.The last column contains the difference in mean values between tech- and non-tech firms. *, **, and *** denote significance at the 1, 5, and 10 percent level, respectively.

Table 2: Summary statistics: financial and patenting variables

Variable	**Obs.**	**Mean**	**Std. dev.**	**Min.**	**Max.**
<u>Financial variables:</u>					
Debt-ratio	44,004	18.413	25.554	0	100
Size (log. assets)	51,719	9.203	2.772	0	19.857
Profitability	39,825	0.040	0.195	-1.50	0.534
Tangibility	51,719	0.236	0.240	0	1
Cash-ratio	48,820	0.126	0.172	0	0.915
Int. burden	26,116	0.265	0.315	0.001	1
Age	49,634	26.7	26.1	1	131
Quoted	51,719	0.053	0.225	0	1
<u>Patent variables:</u>					
Patents filed (p.a.)	51,719	0.426	3.167	0	144
Size patent portfolio	51,719	4.948	37.113	0	2,684
Sum of all offices	51,719	49.552	298.108	0	12,930
Average renewal rate	6,484	7.005	3.373	0	18
Average family size	51,719	6.656	8.903	0	37

Notes: The table displays summary statistics on several financial and patenting measures. All variables are based on average firm-year observations. Respective variables are defined in Table 5. Additionally, this table also displays information on the frequency of renewal payments, firm age, and and binary variable indicating whether a firm is listed on the stock market ('quoted').

Table 3: Sample distribution across sectors (NACE Rev. 2)

Category	**Observations**	**(in %)**
A - Agriculture, forestry, and fishing	261	(0.50)
B - Mining and quarrying	396	(0.77)
C - Manufacturing	28,946	(55.97)
D - Electricity and gas	151	(0.29)
E - Water supply	285	(0.55)
F - Construction	1,965	(3.80)
G - Wholesale and retail trade	6,942	(13.42)
H - Transportation and storage	484	(0.94)
I - Accomodation	147	(0.28)
J - Information and communication	2,136	(4.13)
L - Real estate	621	(1.20)
M - Professional, scientific, technical activities	6,964	(13.47)
N - Administration	1,793	(3.47)
Q - Human health	330	(0.64)
R - Arts, entertainment	298	(0.58)
Total	51,719	(100.00)

Notes: The table displays the distribution of observations in our main sample across sectors according to NACE Rev. 2 main categories, including the percentage as share of total.

Table 4: Summary statistics: tech versus non-tech firms

	Mean values				
	i) **High-tech firm**	ii) **Tech firm**	iii) **Non-tech firm**	**Difference in means (i-iii)**	**Difference in means (ii-iii)**
Debt-ratio	16.150	16.323	21.154	-4.644***	-4.831***
Cash-ratio	0.112	0.106	0.153	-0.041***	-0.047***
Int. burden	0.277	0.270	0.257	0.020***	0.013***
Profitability	0.056	0.060	0.011	0.045***	0.049***
Size (log. assets)	9.820	9.525	8.795	1.025***	0.731***
Size (employees)	1,781.2	1,329.2	1,829.8	-48.6	-500.6***
Fixed asset share	0.304	0.318	0.333	-0.029***	-0.015***
Tangibility	0.188	0.219	0.203	-0.015***	0.016***
Capex ratio	0.763	0.778	0.866	-0.102***	-0.087***
Quoted	0.059	0.051	0.056	0.002	-0.005**
Llt. company	0.739	0.752	0.755	-0.015**	0.003
Patent filings	0.606	0.514	0.314	0.292***	0.200***
Large patent stock	0.160	0.136	0.093	0.068***	0.043***
Patent life (years)	9.003	8.978	9.044	-0.033	-0.066
Active offices (avg.)	7.873	7.888	7.436	0.437***	0.452***
Originality index	0.783	0.782	0.780	0.003	0.002

Notes: The table displays summary statistics on several financial and patenting measures. All variables are based on average firm-year observations. Respective variables are defined in Table 5. Additionally, information on the frequency of renewal payments, firm age, and and binary variable indicating whether a firm is listed on the stock market ('quoted') are displayed. The last two columns contain differences in sector specific means. *, **, and *** denote significance at the 1, 5, and 10 percent level, respectively.

Table 5: Overview capital structure determinants: measurement and predicted impact

Category	**Variable**	**Definition**	**Predicted impact**
Dependent variable:	leverage	$= \frac{\text{long-term debt}}{\text{total debt} + \text{total equity}}$	
Capital structure determinants	size	$= log(\text{total assets})$	positive
	profitability	$= \frac{\text{ebit}}{\text{total assets}}$	negative
	tangibility	$= \frac{\text{tangible-fixed assets}}{\text{total assets}}$	positive
	cash	$= \frac{\text{total cash}}{\text{total assets}}$	negative
Patent variables:	patent filling	$= \sum \text{patent filings}_{it}$	-
	portfolio size (PS)	$= \sum \text{active patent(s)}_{it}$	-
	family size (FS)	$= \sum \text{patent offices}_{pit}$	-
	patent stock	$= FS_{it} \times PS_{it}$	positive

Notes: The table displays definitions of all variables included in the baseline model specified in Equation (1), including their predicted impact on leverage. Patent variables are further normalized in all empirical analyses by the 2-digit-industry-year specific maximum. The indices on the patent-related variables refer to the patent application p of firm i in year t. Once firm i files more than one patent in a given year, the unweighted average of the respective measures is calculated.

Table 6: Baseline regression: capital structure determinants and patenting

Dependent variable:	Debt-ratio					
Portfolio value:	All				High	Low
	(I)	(II)	(III)	(IV)	(V)	(VI)
Patent stock		21.283**				
		(10.228)				
Patent filings			2.084			
			(1.306)			
Stock size				9.606*	11.896**	-6.193
				(4.922)	(5.361)	(4.029)
Size	1.091**	1.069**	1.063**	1.095**	1.211*	1.162
	(0.517)	(0.517)	(0.518)	(0.517)	(0.639)	(0.816)
Profitability	-13.092***	-13.137***	-13.117***	-13.099***	-11.783***	-14.616***
	(1.796)	(1.797)	(1.794)	(1.796)	(2.920)	(2.383)
Tangibility	9.631***	9.740***	9.744***	9.647***	5.140	12.183***
	(2.075)	(2.028)	(2.034)	(2.070)	(4.271)	(2.669)
Cash	-2.559	-2.614	-2.587	-2.562	-4.791	-3.501
	(1.711)	(1.711)	(1.710)	(1.712)	(2.747)	(2.363)
Constant	-5.375	-5.508	-5.598	-5.488	-7.124	-5.545
	(5.173)	(5.161)	(5.165)	(5.171)	(6.724)	(7.955)
Additional controls:						
Firm-FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year-FE	Yes	Yes	Yes	Yes	Yes	Yes
Lagged dep. var.	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.22	0.22	0.22	0.22	0.17	0.21
Observations	14,712	14,712	14,712	14,712	5,296	9,416

Notes: The table presents estimates from regressions explaining leverage firms' debt ratios as defined in Table 5 which also specifies the applied capital structure determinants. All regressions control for unobserved heterogeneity by including firm- and country-year fixed-effects as well as additionally including the lagged dependent variable. Patent stock refers to the size and value of firms' patent portfolio, while stock size refers only to the quantitative dimension of the patent portfolio. Patent filings refer to the number of patents filed in a given year. Patent variables are normalized on a year-industry basis and included with their lag of one period. High and low portfolio value (Columns IV and V) refers to firms with an above, respectively below, average patent value measure. Standard errors (in parentheses below coefficients) are heteroscedasticity-consistent and clustered at the firm level. *, **, and *** denote significance at the 1, 5, and 10 percent level, respectively.

Table 7: Extension: broad versus specific patent portfolios

Dependent variable:	Debt-ratio			
Patent originality:	Specific	Broad		
		$Q66$	$Q33$	$Q25$
	(I)	(II)	(III)	(IV)
Patent stock	-26.496	17.362*	30.390*	58.665***
	(44.051)	(10.335)	(17.179)	(6.461)
Size	1.963*	0.721	2.560**	1.523
	(1.100)	(0.878)	(1.173)	(1.613)
Profitability	-13.562***	-13.185***	-9.103***	-9.391***
	(4.406)	(2.437)	(3.192)	(3.045)
Tangibility	15.413***	7.018**	11.391**	14.614**
	(5.477)	(3.336)	(5.271)	(6.308)
Cash	-5.735	-5.985**	-8.741***	-6.054
	(3.747)	(2.595)	(3.032)	(3.718)
Constant	-12.799	-0.673	-19.457*	-9.761
	(10.304)	(8.917)	(11.317)	(15.325)
Additional controls:				
Firm-FE	Yes	Yes	Yes	Yes
Country-Year-FE	Yes	Yes	Yes	Yes
Lagged dep. var	Yes	Yes	Yes	Yes
R^2	0.19	0.18	0.24	0.22
Observations	3,360	6,517	3,065	2,307

Notes: The table presents estimates from panel regressions explaining debt-ratios of sample firms in the technology sector. All variables and their use are defined as specified in Table 5 and Equation (1). We split the sample in the subgroups according to the specificity of their patent portfolios, i.e. specific (Column I) and broad patent portfolios (Columns II-IV). Patent portfolios are defined as specific, if they refer to only one distinct technology class. They are defined as broad if they refer to more than one technology class and lay above the 66th-, 33rd, and 25th-percentile of the originality index distribution. Lower percentiles reflect broader patent portfolios. The use of additional controls is indicated in respective rows below the coefficients. Standard errors (in parentheses below coefficients) are heteroscedasticity-consistent and clustered at the firm level. *, **, and *** denote significance at the 1, 5, and 10 percent level, respectively.

Table 8: Extension: tech versus non-tech firms

Dependent variable:	Debt-ratio			
Sectors:	Tech	Non-tech	All:	
	(I)	(II)	(III)	(IV)
Patent stock	21.248**	1.016	8.822*	1.143
	(10.282)	(2.659)	(5.017)	(2.592)
P × Tech firm				20.308*
				(10.560)
Size	1.069**	1.496**	1.304***	1.288***
	(0.517)	(0.761)	(0.452)	(0.452)
Profitability	-13.137***	-6.588***	-9.629***	-9.624***
	(1.797)	(2.406)	(1.590)	(1.589)
Tangibility	9.740***	14.391***	11.543***	11.612***
	(2.028)	(3.063)	(1.760)	(1.751)
Cash	-2.614	-7.282***	-5.143***	-5.152***
	(1.711)	(2.353)	(1.461)	(1.462)
Constant	-5.508	-7.597	-7.118	-7.014
	(5.161)	(7.298)	(4.423)	(6.522)
Additional controls:				
Firm-FE	Yes	Yes	Yes	Yes
Country-Year-FE	Yes	Yes	Yes	Yes
Lagged dep. var	Yes	Yes	Yes	Yes
R^2	0.22	0.20	0.21	0.21
Observations	14,712	9,024	23,736	23,736

Notes: The table presents estimates from panel regressions explaining debt-ratios of sample firms. All variables and their use are defined as specified in Table 5 and Equation (1). We split the sample in the subgroups according to their industry-specification: Only tech-firms (Column I), non-tech firms (Column II), and the full sample (Columns III-IV). Definitions on the sectoral affiliation are in accordance with Eurostat (2018). Column IV includes an interaction term of the patent measure with a dummy variable indicating sectoral affiliation. The single regressors indicating firm sectors in these cases is omitted, because of perfect multicollinearity arising from the inclusion of firm-level fixed effects. The use of additional controls is indicated in respective rows below the coefficients. Standard errors (in parentheses below coefficients) are heteroscedasticity-consistent and clustered at the firm level. *, **, and *** denote significance at the 1, 5, and 10 percent level, respectively.

Table 9: Regression estimates: Enforcement Directive, patent stock, and leverage

Dependent variable:	Debt-ratio					
Sectors:	All				Tech	Non-tech
	(I)	(II)	(III)	(IV)	(V)	(VI)
P × Post × Tech firm				19.020**		
				(9.642)		
P × Post			19.063***	8.212*	24.785***	8.323*
			(5.929)	(4.551)	(7.576)	(4.829)
Patent stock (P)	9.048*	9.048*	2.812	3.140	10.911	-1.181
	(5.187)	(5.187)	(3.266)	(2.984)	(6.700)	(2.633)
Post		3.415***	3.160***	3.153***	3.538***	2.428*
		(0.730)	(0.728)	(0.727)	(0.838)	(1.306)
Size	0.958***	0.958***	0.960**	0.962**	0.874*	0.986
	(0.453)	(0.453)	(0.453)	(0.453)	(0.516)	(0.761)
Profitability	-9.634***	-9.634***	-9.592***	-9.613***	-12.972***	-6.648***
	(1.626)	(1.626)	(1.625)	(1.626)	(1.833)	(2.466)
Tangibility	10.845***	10.845***	10.877***	10.898***	9.765***	12.855***
	(1.829)	(1.829)	(1.814)	(1.810)	(2.040)	(3.204)
Cash	-5.119***	-5.119***	-5.110***	-5.122***	-2.600	-7.287***
	(1.518)	(1.518)	(1.518)	(1.519)	(1.765)	(2.470)
Constant	-3.628	-5.930	-5.970	-5.973	-6.227	4.104
	(4.436)	(4.285)	(4.283)	(4.281)	(5.023)	(6.985)
Additional controls:						
Firm-FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year-FE	Yes	Yes	Yes	Yes	Yes	Yes
Time trend	Yes	Yes	Yes	Yes	Yes	Yes
Lagged dep. var.	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.20	0.20	0.20	0.20	0.22	0.18
Observations	22,727	22,727	22,727	22,727	14,107	8,620

Notes: The table presents estimates from regressions explaining firms' debt ratios. The use of controls as defined in Table 5 is indicated in the bottom of the table. The estimations capture the effect of the implementation of the Enforcement Directive with Column IV specifying Equation (2). We sequentially introduce to baseline specification (Column I) as speficied in Equation (1) the country-specific treatment dummy equal to one after the implementation of the directive (Column II) and the interaction of both (Column III). In the last two columns, the sample is split according to whether a firm belongs to the tech sector (Column V) or not (Column VI). The displayed time variant variables used for the DID estimation (*patent stock* and *post*) are included by using their first lag. Compared to the baseline regression, we exclude Belgium, because the country effectively did not adopt the Enforcement Directive. Standard errors (in parentheses below coefficients) are heteroscedasticity-consistent and clustered at the firm level. *, **, and *** denote significance at the 1, 5, and 10 percent level, respectively.

Table 10: Plausibility analysis: the announcement effect

Dependent variable:	Debt-ratio				
Sectors:	All			Tech	Non-tech
	(I)	(II)	(III)	(IV)	(V)
P × A × Tech firm			10.903		
			(7.721)		
P × Announcement (A)		6.984	2.317	12.054	4.265
		(4.475)	(4.700)	(8.049)	(4.944)
Patent stock (P)	1.455	-1.213	-0.862	-2.822	-1.109
	(3.450)	(3.872)	(3.697)	(9.641)	(3.388)
Additional controls:					
Firm-level	Yes	Yes	Yes	Yes	Yes
Firm-FE	Yes	Yes	Yes	Yes	Yes
Country-Year-FE	Yes	Yes	Yes	Yes	Yes
Time trend	Yes	Yes	Yes	Yes	Yes
Lagged dep. var	Yes	Yes	Yes	Yes	Yes
R^2	0.12	0.12	0.12	0.12	0.13
Observations	16,065	16,065	16,065	9,856	6,209

Notes: The table presents estimates from regressions explaining firms' debt ratios in our *placebo* setup. All variables and regression specifications follow those in Table 9. Unlike in our other regression, we use the indicator variable *Announcement*, which equals one after the Enforcement Directive was decided upon by the European Parliament and the Council as of April 29$^{\text{th}}$, 2004. We sequentially introduce the patent stock (Column I), its interaction with the placebo event (Column II), and the tripple interaction with the tech sector indicator (Column III). The last two columns split our sample according to the previously defined tech firms (Column IV) and non-tech firms (Column V). The coefficient estimate on the interaction terms is the coefficient of interest, measuring the impact of the placebo event for large, high value patent stocks. For consistency, we only consider years *before* the Enforcement Directive was actually implemented in respective countries. All displayed time-variant regressors are included by using their first lag. Standard errors (in parentheses below coefficients) are heteroscedasticity-consistent and clustered at the firm level. *, **, and *** denote significance at the 1, 5, and 10 percent level, respectively.

Table 11: The effect of patenting on interest burden

Dependent variable:	Interest burden					
Portfolio value:	All				High	Low
	(I)	(II)	(III)	(IV)	(V)	(VI)
Patent stock		-0.240**				
		(0.106)				
Patent filings			-0.043**			
			(0.020)			
Stock size				-0.100*	-0.242***	0.075
				(0.056)	(0.090)	(0.069)
Size	-0.030***	-0.030***	-0.030***	-0.030***	-0.034*	-0.024**
	(0.009)	(0.009)	(0.009)	(0.009)	(0.018)	(0.012)
Profitability	0.037	0.037	0.037	0.037	0.035	0.015
	(0.027)	(0.027)	(0.027)	(0.027)	(0.052)	(0.032)
Tangibility	-0.164***	-0.163***	-0.164***	-0.163***	-0.065	-0.143***
	(0.040)	(0.040)	(0.040)	(0.040)	(0.085)	(0.047)
Cash	-0.056	-0.054	-0.055	-0.055	-0.150**	0.003
	(0.037)	(0.037)	(0.037)	(0.037)	(0.068)	(0.043)
Constant	0.493***	0.495***	0.496***	0.493***	0.583***	0.418***
	(0.095)	(0.095)	(0.095)	(0.095)	(0.187)	(0.117)
Additional controls:						
Firm-FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year-FE	Yes	Yes	Yes	Yes	Yes	Yes
Lagged dep. var.	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.26	0.27	0.26	0.26	0.18	0.25
Observations	10,446	10,446	10,446	10,446	3,816	6,630

Notes: The table presents estimates from regressions explaining the costs of obtaining external funding, i.e. the interest burden of a firm. The set of regressions repeat the baseline specification as specified by Equation (1) and regressors are defined analogeously as defined in Table 5. The use of additional controls is indicated in respective rows below the coefficients. Standard errors (in parentheses below coefficients) are heteroscedasticity-consistent and clustered at the firm level. *, **, and *** denote significance at the 1, 5, and 10 percent level, respectively.

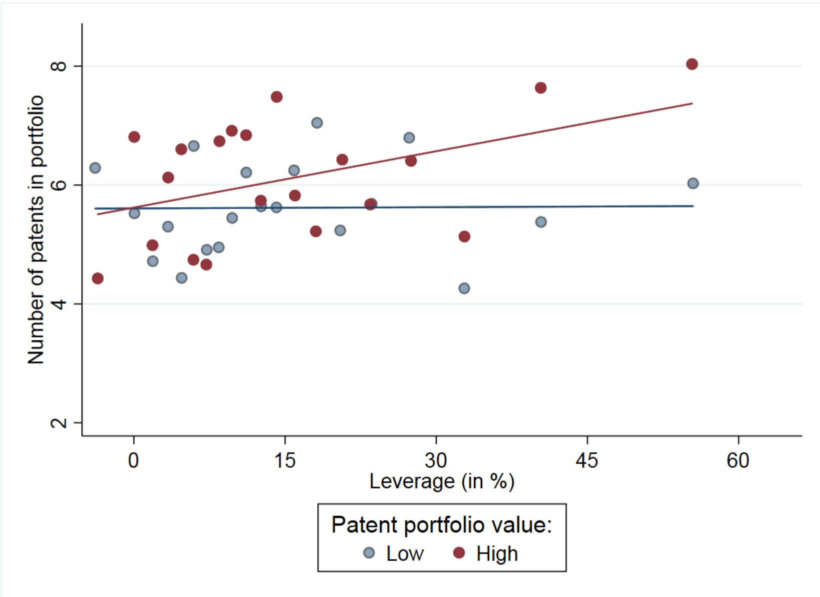
Table 12: The Enforcement Directive's effect on interest burden

Dependent variable:	Interest burden				
Sector:	All			Tech	Non-tech
	(I)	(II)	(III)	(IV)	(V)
PP × Tech firm			-0.240**		
			(0.116)		
P × Post (PP)		-0.089	0.036	-0.172*	0.006
		(0.067)	(0.087)	(0.099)	(0.087)
Patent stock (P)	-0.068	-0.020	-0.041	-0.143	0.016
	(0.060)	(0.058)	(0.057)	(0.108)	(0.067)
Post	0.030	0.031	0.032	0.021	0.045
	(0.033)	(0.033)	(0.033)	(0.800)	(0.053)
Additional controls:					
Firm-FE	Yes	Yes	Yes	Yes	Yes
Country-Year-FE	Yes	Yes	Yes	Yes	Yes
Lagged dep. var.	Yes	Yes	Yes	Yes	Yes
R^2	0.21	0.21	0.22	0.24	0.19
Observations	14,517	14,517	14,517	9,333	5,184

Notes: The table presents estimates from regressions explaining the costs of obtaining external funding, i.e. the interest burden of a firm. The estimations capture the effect of the implementation of the Enforcement Directive as a positive shock to the value of firms' patent portfolio and are therefore structured just in the augmented baseline specification, Equation (2). In the last two columns, the sample is split according to whether a firm belongs to the tech sector (Column IV) or not (Column V). The use of additional controls is indicated in respective rows below the coefficients. The displayed time variant variables used for the DID estimation (*patent stock* and *post*) are included by using their first lag. Standard errors (in parentheses below coefficients) are heteroscedasticity-consistent and clustered at the firm level. *, **, and *** denote significance at the 1, 5, and 10 percent level, respectively.

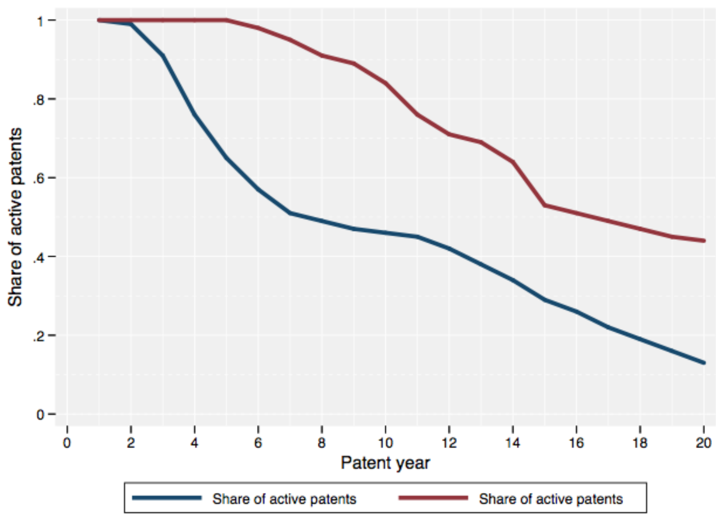
Figures from the main part:

Figure 1: Binned scatterplot: portfolio size and leverage by patent value



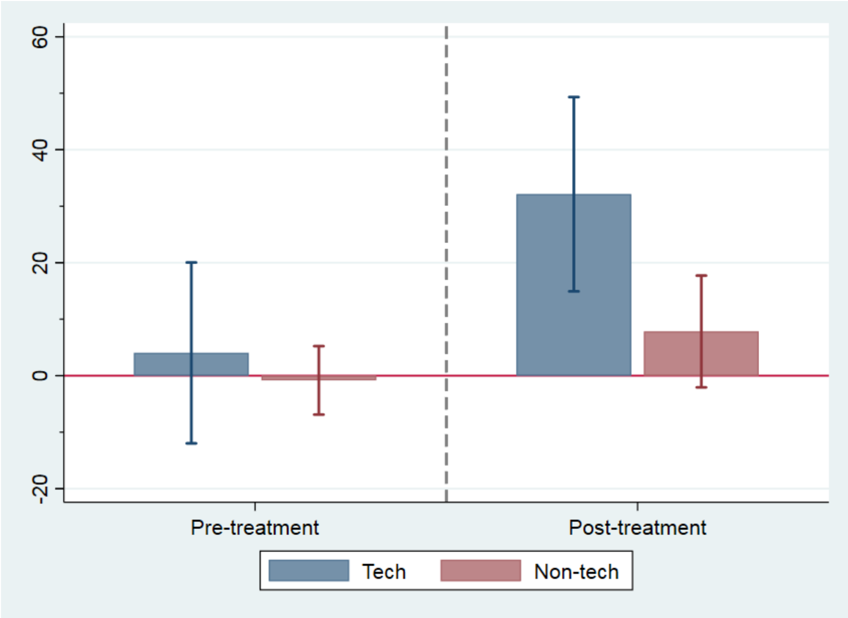
Notes: This binned scatterplot relates the number of actively held patents (y-axis) to leverage ratios (x-axis) for our sample of manufacturing firms. The plot displays the values and the linear fit according to whether firms' patent stock is of high or low value. The value is considered as high, if the average patent value of a firms' patent portfolio is above the overall median value. Otherwise the value is classified as low. The number of bins in each subgroup is set to 20.

Figure 2: Share of active patents by patent year: EPO versus USPTO



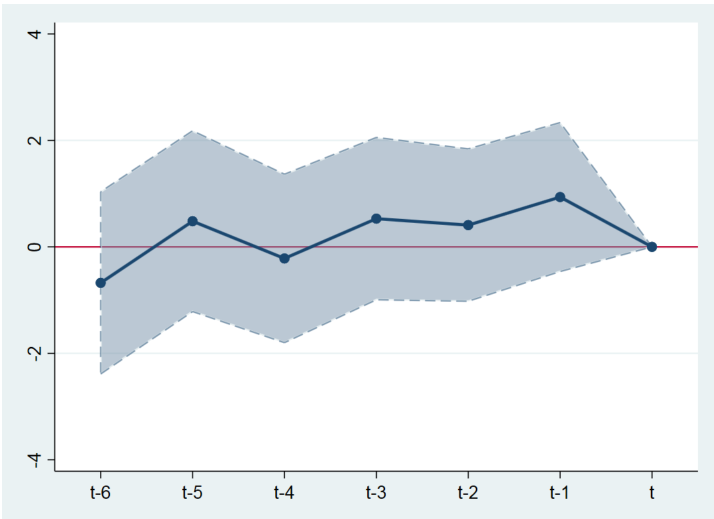
Notes: This figure compares the rate of granted patent registrations existing and in force each patent year starting with the year of application, with a maximum of 20 years. We differentiate among patents filed at EPO and at USPTO, where differing payment fee schedules apply. The EPO shares represent a weighted average ratio of patent renewals made for European patents in the EPC states. Data is obtained from IP5 (2018). The reference year is 2010, which is representative for our sample period.

Figure 3: Patent portfolio values and leverage: pre- and post treatment comparison



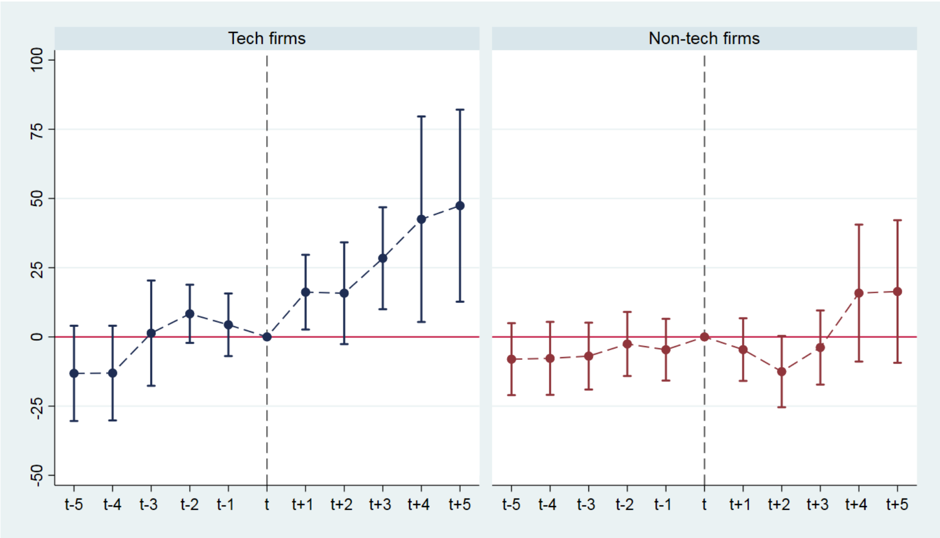
Notes: This figure plots correlation coefficients of the patent portfolio measure both before and after the treatment phase. Treatment refers to the implementation of the Enforcement Directive, i.e. firms are treated after the law is transposed in the country they are located in. We estimate the augmented baseline specification, Equation (2), on tech and non-tech firms separately. The bars resemble the size of the coefficient on our patent portfolio measure for respective firms, respectively its interaction with the treatment dummy. Whiskers represent the 90 percent confidence intervals.

Figure 4: Deviation in parallel trends during pre-treatment period



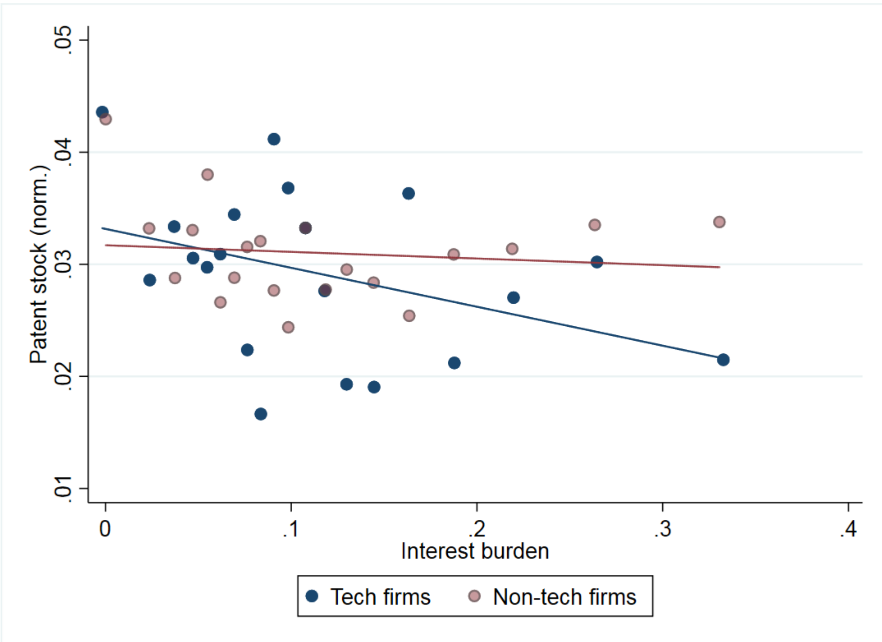
Notes: This figure plots correlation coefficients of the interaction terms of year dummies that indicate the year before the implementation of the Enforcement Directive in the respective country with the binary indicator on whether the firm is in the tech sector or not. These regressors are estimated within in the augmented baseline regression setup from Equation (2). Thus, coefficients represent the difference in the paths between tech and non-tech firms in the difference-in-difference setup. The shaded area represents the 95 percent confidence intervals of the estimates. Because we analyse the pre-treatment period, the estimation excludes any observation from the years after the country-specific implementation year of the Enforcement Directive. This implementation year, t, marks the reference year in this graph.

Figure 5: Coefficient plot: portfolio value and leverage across years



Notes: This figure depicts the impact of patent portfolios on firms' leverage before and after the treatment, i.e. the adoption of the Enforcement Directive. Implementation dates vary across countries. The plot shows the coefficients, α^{t}_{dc} (left hand) and α^{nt}_{dc} (right hand), of the two individual regressions for $s = t$ and $t = nt$: $Leverage_{it} = \vartheta_i + \eta_{ct} + \alpha^{s}_{dc}\,(sector^{s}_{i} \cdot patent\,stock_{it} \cdot Enforcement_{t+d\,c}) + \beta\,determinants_{it} + u_{it}$, with $dc \in [-5, 5]$ resembling the year d before/after the implementation of the Enforcement Directive in country c. $Sector^{s}_{i}$ with $s \in [t, nt]$ is a dummy variable equal to one if the firm is in the tech sector (i.e. for $s = t$) or if the firm is *not* in the tech sector (i.e. for $s = nt$) and zero otherwise. The remaining variables are specified as above. Whiskers represent the 90 percent confidence intervals of the estimates.

Figure 6: Binned scatterplot: portfolio value and interest burden



Notes: This binned scatterplot relates the normalized patent stock measure (y-axis) to firms' interest burden (x-axis). The plot displays the values and the linear fit according to firms' sectoral affiliation, i.e. whether they are from a tech-sector or not. The number of bins in each subgroup is set to 20. The plot simultaneously controls for the confounding factors capital structure determinants and country-year fixed effects analogue to the baseline specification in Equation (1).

Appendix A:

On the legal foundation

The following descriptions illustrate that the European legal system provides the legal basis for the use of patents as a mean for securing loans. Intellectual property rights, such as patents, are ownership rights and therefore subject to be transferred, limited or pledged through legal transaction (McGuire *et al.* 2006). Articles 71-74 of the European Patent Convention (EPC) govern that all rights derived from a patent are transferable, both in a restricted or unrestricted manner. Potentially, even future inventions can be transfered to the extent that they are already determined with sufficient certainty and assignable to the individual contracts (Mes 2015).

Moreover, formal intellectual property rights are regulated by the law of the country where rights are registered. As such, in a European context, several country-specific rules determine the use of patents. For a non-exhaustive list of examples on the largest European economies, consider the following: 1) in Italy securities and special privileges over patents are expressly allowed for monetary credits by articles 138 and 140 of the Italian Code on Intellectual Property (Legislative Decree no. 30/2005). 2) In France, pledges ('*nantissement*') over patents are governed by Articles L 142-1 following the French Commercial Code and are effective, under L 143-17, upon registration with National Institute for Industrial Property. 3) In Spain, patents as well as their registration requests can be given as security. The security is binding against third parties of good faith if it is duly registered in the Spanish Patent and Trademarks Register (Article 46 of Law 17/2001; Articles 74 and 79 of Law 11/1986). Finally, 4) in Germany, transfers of patents is governed by Article 15(1) Sentence 2 of the PatG.

In accordance to existing law, patents qualify to serve as a mean of collateralization in a debt contract through assignment either by way of factual securitization or pledging (Maume 2017). A patent holding firm is thus entitled to relinquish its patent rights with a material transfer agreement to the loan-issuing bank. From a legal perspective, in principal, the transfer merely demands a documented mutual consent of the parties involved in order to become effective (Mes 2015). In case of none performance of the loan or insolvency of the borrower, the bank could then withhold all rights associated with the respective patents (Stürner 2018).[17]

[17]In practical terms, a factual transfer appears implausible. Firms mostly need their patents for maintaining operations, particularly in the case valuable patents. In contrast, capital providers are not likely to utilize the

Instead of a factual transfer, the pledging of intellectual rights is the second potential mode through which patents can be utilized as collateral. In this case, the contract contains a conditional obligation to transfer the collateral security, once pre-specified conditions are met (McGuire *et al.* 2006). Specifically, pledging does not assign the creditor with any right of use the respective security. The right of use remains exclusively in the sphere of the pledging party. Again, from a legal perspective only a documented mutual consent is required for a pledge to become effective.

property rights for their own operations. One way to circumvent this issue is an immediate (and exclusive) licensing agreement, which ensures the continuation of the collateral providers business activities. Another possibility is to postpone the factual transfer by entrenching default as a necessary condition for the re-assignment to become effective.

Appendix B: Tables (A1-A14)

Table A1: Overview on high-, medium-, and low-tech classifications

Manufacturing industries	NACE Rev. 2 codes	– Definitions
High-technology	21	Manufacture of basic pharmaceutical products and pharmaceutical preparations
	26	Manufacture of computer, electronic and optical products
Medium-high-technology	20	Manufacture of chemicals and chemical products
	27-30	Manufacture of electrical equipment; Manufacture of machinery and equipment n.e.c.; Manufacture of motor vehicles, trailers and semi-trailers; Manufacture of other transport equipment
Medium-low-technology	19	Manufacture of coke and refined petroleum products
	22-25	Manufacture of rubber and plastic products; Manufacture of other non-metallic mineral products; Manufacture of basic metals; Manufacture of fabricated metals products, excepts machinery and equipment
	33	Repair and installation of machinery and equipment
Low-technology	10-18	Manufacture of food products, beverages, tobacco products, textile, wearing apparel, leatherand related products, wood and of products of wood, paper and paper products, printing and reproduction of recorded media
	31-32	Manufacture of furniture; Other manufacturing

Notes: The table indicates the classification into high-, medium-, and low-tech firms. We follow the sectoral classfication approach as proposed by Eurostat (2018). This aggregation of the manufacturing industries relies on each industries level of technological intensity (i.e. R& D expenditure as a share of value added). NACE Rev. 2 industry classifications are used on the 2-digit level.

Table A2: Distribution of observations across countries

Country	Observations	(in %)
Belgium	1,567	(3.03)
Denmark	1,102	(2.13)
Finland	1,537	(2.97)
France	8,932	(17.27)
Germany	15,420	(29.81)
Ireland	559	(1.08)
Italy	182	(0.35)
Netherlands	1,227	(2.37)
Sweden	3,571	(6.90)
United Kingdom	17,622	(34.07)
Total	51,719	(100.00)

Notes: The table displays the distribution of observations in our main sample across different countries. Due to irregular coverage across the historical excerpts of the Amadeus database Austria, Greece, Luxembourg, Portugal, and Spain are not included in the sample.

Table A3: Summary of the Enforcement Directive (2004/48/EC)

	General topic	**Summary**
Article 1-2	Subject matter & scope	State the general objectives and legal boundries of the Directive
Article 3-5	General provisions	Define the general principle (provide 'fair and equitable measures'), appilcable right holders, and lays out the principles of authorship and ownership
Article 6-7	Collection of evidence	Set out a number of obligations with regard to gathering and preserving evidence
Article 8	Right to information	Specifies that courts may order disclosure of origin and distribution networks of infringing goods/services
Article 9	Provisional measures	Specifies that courts may issue interlocutory injunctions and other precautionary seizures
Article 10 - 12	Final remedies	Specify corrective measures and alternative (recurring) penalty payments for non-compliance
Article 13-14	Damages & Costs	Specifies compensation for damaged entity, if infringement is "*knowingly, or with reasonable grounds to know*" and court payments
Article 15	Publication	Specifies publication of verdicts
Article 16	National duties	Defines sanctions for member states in case of non-implementation of rules

Notes: This table summarizes the main Articles of the Directive 2004/48/EC of the European Parliament and of the Council of April, 29th 2004 on the enforcement of intellectual property rights, the so-called Enforcement Directive. Its overall objective is to "ensure a high, equivalent and homogenous level of protextion in the internal market" (recital 10) by ensuring minimum standards of IP right enforcement. The intended deadline for implementation was April, 29th 2006.

Table A4: Implementation dates of Enforcement Directive by sample country

Country	**Implementation date**
Denmark	04/2006
Finland	04/2006
France	06/2008
Germany	07/2008
Ireland	04/2006
Italy	04/2006
Netherlands	05/2007
Sweden	04/2009
United Kingdom	04/2006

Notes: This table displays the implementation dates of the Directive 2004/48/EC across member states. The intended deadline for implementation was April 29th, 2006. However, EU Directives only enter into force after passing domestic parliaments, which leads to significant variation in actual implementation dates. Belgium is not included in this list, as the Directive cannot be considered as being transposed into domestic legislation. Hence, the country is also excluded in estimations that draw on the Enforcement Directive.

Table A5: Baseline regression using alternative definitions of the dependent variable

Dependent variables:	Alternative leverage proxies			
	(I)	(II)	(III)	(IV)
Patent stock	21.248**	22.460**	18.047**	2.000**
	(10.282)	(9.678)	(9.053)	(0.940)
Additional controls:				
Firm-level determinants	Yes	Yes	Yes	Yes
Firm-FE	Yes	Yes	Yes	Yes
Country-Year-FE	Yes	Yes	Yes	Yes
Lagged dep. var	Yes	Yes	Yes	Yes
R^2	0.22	0.27	0.22	0.29
Observations	14,712	14,712	14,712	10,139

Notes: The table presents estimates from regressions on different measures financial leverage. Column I-III use different specifications of firms' the long-run debt-to-asset ratio. Column I uses truncated values, Column II uses non-cleaned variables, and Column III uses windsorized values. In addition to this, in Column IV we use the logarithm of total long-term debt as dependent variable. All regressions include firm-level capital structure determinants, firm- and country-year-fixed effects as well as the lagged dependent variable. All variables are defined in Table 5. Estimates on the coefficients of these variables are omitted but their usage is indicated in the table. The main regressor, patent stock, is normalized on a year-industry basis and included with its lag of one period. Standard errors (in parentheses below coefficients) are heteroscedasticity-consistent and clustered at the firm level. *, **, and *** denote significance at the 1, 5, and 10 percent level, respectively.

Table A6: Baseline regression using alternative definitions of the main regressor

Dependent variable:	Debt-ratio				
	(I)	(II)	(III)	(IV)	(V)
Patent stock proxies	21.248**	0.006**	0.003***	0.001***	0.176*
	(10.282)	(0.003)	(0.001)	(0.000)	(0.096)
Additional controls:					
Firm-level determinants	Yes	Yes	Yes	Yes	Yes
Firm-FE	Yes	Yes	Yes	Yes	Yes
Country-Year-FE	Yes	Yes	Yes	Yes	Yes
Lagged dep. var	Yes	Yes	Yes	Yes	Yes
R^2	0.22	0.22	0.22	0.22	0.22
Observations	14,712	14,712	14,712	14,712	14,712

Notes: The table presents estimates from regressions on firms' financial leverage as measured by the long-term debt ratio. All regressions include firm-level capital structure determinants, firm- and country-year-fixed effects as well as the lagged dependent variable. All variables are defined as specified in the main part. Estimates on the coefficients of these variables are omitted but their usage is indicated in the table. The definition of the main regressor, patent stock, alters in each specification but always comprises the two dimensions of patent stock size and value. Column I uses the standard, normalized measure as deployed for the baseline regressions. Column II-IV use non-normalized values: Column II uses truncated values, Column III raw data, Column IV uses the total number of the family size measure. Column V uses a the logarithm of the normalized specification. All measures are included with their one period lag. Standard errors (in parentheses below coefficients) are heteroscedasticity-consistent and clustered at the firm level. *, **, and *** denote significance at the 1, 5, and 10 percent level, respectively.

Table A7: Baseline regression using different lead/lag levels

Dependent variable:	Debt-ratio					
Lead/ lag-level:	Lead (t+2)	Lead (t+1)	(t)	Lag(t-1)	Lag(t-2)	Lag(t-3)
	(I)	(II)	(III)	(IV)	(V)	(VI)
Patent stock	7.937	14.305	17.406*	21.248**	14.145*	6.260
	(7.681)	(9.154)	(9.781)	(10.282)	(7.823)	(6.109)
Additional controls:						
Firm-level determinants	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. var	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.18	0.21	0.22	0.22	0.21	0.21
Observations	12,016	13,308	14,712	14,712	12,839	11,061

Notes: The table presents estimates from regressions on firms' debt ratios as specified in Equation (1). All variables are defined in Table 5. Estimates on the control variables are omitted but their usage is indicated in the table. In the baseline regression (here Column IV), we use the one year lag of the main regressor, patent stock. We repeat the regressions using different lead and lag levels as indicated the header 'lead-/lag-level'. Standard errors (in parentheses below coefficients) are heteroscedasticity-consistent and clustered at the firm level. *, **, and *** denote significance at the 1, 5, and 10 percent level, respectively.

Table A8: Broad versus specific patents in non-tech sectors

Dependent variable:	Debt-ratio			
Patent originality:	Specific	Broad		
		$Q66$	$Q33$	$Q25$
	(I)	(II)	(III)	(IV)
Patent stock	-2.028	7.019	18.136	16.278
	(10.157)	(7.256)	(14.211)	(12.399)
Additional controls:				
Firm-level	Yes	Yes	Yes	Yes
Firm-FE	Yes	Yes	Yes	Yes
Country-Year-FE	Yes	Yes	Yes	Yes
Lagged dep. var	Yes	Yes	Yes	Yes
R^2	0.20	0.18	0.17	0.16
Observations	3,949	6,808	3,563	2,747

Notes: The table presents estimates from panel regressions explaining debt-ratios. Estimations are equivalent to those in Table 7 with the difference that this time, regressions are estimated for the subsample of non-tech firms only. We split the sample in the subgroups according to the specificity of their patent portfolios with regard to the originality index of patents, i.e. specific (Column I) and broad patent portfolios (Columns II-IV). Patent portfolios are defined as specific, once they have refer to only one distinct technology class. They are defined as broad if they refer to more than one technology class and above the 66^{th}-, 33^{rd}, and 25^{th}-percentile, respectively. The use of additional controls is indicated in respective rows below the coefficients. Standard errors (in parentheses below coefficients) are heteroscedasticity-consistent and clustered at the firm level. *, **, and *** denote significance at the 1, 5, and 10 percent level, respectively.

Table A9: Assessment of anticipatory effects (pre-treatment)

Dependent variable:	Debt-ratio				
Pre-treatment sample	Full sample			Tech	Non-tech
(Additional interaction)	(Tech)	(Non-tech	(None)	(None)	(None)
	(I)	(II)	(III)	(IV)	(V)
$t-6$	-4.489	-4.312	-5.112	-8.285	-5.320
	(11.606)	(5.366)	(6.534)	(10.738)	(6.190)
$t-5$	-10.259	-3.962	-7.279	-12.184	-3.790
	(9.540)	(3.783)	(4.684)	(9.720)	(4.415)
$t-4$	-10.695	-0.265	-5.611	-15.771**	3.228
	(7.260)	(5.449)	(4.892)	(7.185)	(6.122)
$t-3$	-10.331	1.593	-3.946	-14.145*	3.399
	(7.306)	(4.935)	(4.658)	(7.357)	(5.223)
$t-2$	4.405	1.619	2.331	0.840	4.315
	(7.743)	(5.074)	(4.808)	(8.138)	(5.604)
$t-1$	6.373	-0.308	2.500	3.198	1.699
	(4.730)	(5.094)	(3.633)	(4.435)	(5.662)
Additional controls:					
Firm-level determinants	Yes	Yes	Yes	Yes	Yes
Firm-FE	Yes	Yes	Yes	Yes	Yes
Country-Year-FE	Yes	Yes	Yes	Yes	Yes
Lagged dep. var	Yes	Yes	Yes	Yes	Yes
R^2	0.13	0.13	0.13	0.13	0.13
Observations	17,391	17,391	17,391	10,671	6,720

Notes: The table presents estimates from regressions explaining firms' debt ratios. The regression is based on the baseline specification, Equation (1), and additionally contains interaction terms of the patent stock variable with a country-specific year indicator equal to one in the respective years (1-6) before the implementation of the Enforcement Directive, denoted as $t-j$ ($\forall j \in [1,6]$). This interaction term is multiplied with a binary indicator equalling one if the firm is from the tech sector (Column I), in the non-tech sector (Column II), or no additional interaction is used (Column III). Further, the sample is split according to tech-firms (Column IV) and non-tech firms (Column V). The sample is truncated by exluding firm-year observations in all years succeeding the implementation year of the Enforcement Directive in the corresponding countries. The use of controls is indicated in the bottom of the table. Standard errors (in parentheses below coefficients) are heteroscedasticity-consistent and clustered at the firm level. *, **, and *** denote significance at the 1, 5, and 10 percent level, respectively.

Table A10: Testing for pre-treatment trends

Dependent variables:	Debt-ratio			
	(I)	(II)	(III)	(IV)
Trend × medium-/low tech firm				0.120
				(0.102)
Trend × hightech firm			0.026	
			(0.111)	
Trend × tech firm		0.138		
		(0.112)		
Time trend	-0.130**	-0.220**	-0.139**	-0.169**
	(0.057)	(0.097)	(0.067)	(0.069)
Additional controls:				
Firm-level determinants	Yes	Yes	Yes	Yes
Firm-FE	Yes	Yes	Yes	Yes
Lagged dep. var	Yes	Yes	Yes	Yes
R^2	0.12	0.12	0.12	0.12
Observations	18,762	18,762	18,762	18,571

Notes: The table presents estimates from regressions on firms' debt ratios for the pre-treatment subsample. The time trend variables is a running number for each year during that period. In Columns II-IV this continuous measure is interacted with an indicator variable equal to one if the firm is from the tech sector (Column II), the high-tech sector (Column III), or the medium- low-tech sector (Column IV). All regressions include firm-level capital structure determinants defined in Table 5, firm-fixed effects as well as the lagged dependent variable. Estimates on the coefficients of these variables are omitted but their usage is indicated in the table. Standard errors (in parentheses below coefficients) are heteroscedasticity-consistent and clustered at the firm level. *, **, and *** denote significance at the 1, 5, and 10 percent level, respectively.

Table A11: Lag structure of the regression estimates (post-treatment)

Dependent variable:	Debt-ratio				
Post-treatment sample	Full sample			Tech	Non-tech
(Additional interaction)	(Tech)	(Non-tech	(None)	(None)	(None)
	(I)	(II)	(III)	(IV)	(V)
$t+1$	13.168***	-0.392	7.879**	12.608***	2.063
	(4.790)	(5.565)	(3.819)	(5.403)	(5.354)
$t+2$	20.339**	1.504	14.380**	20.016**	5.112
	(8.010)	(5.848)	(5.802)	(7.827)	(5.534)
$t+3$	16.534**	-3.440	10.294*	15.628**	1.525
	(7.450)	(5.529)	(5.325)	(7.650)	(4.643)
$t+4$	33.278***	10.192	27.945***	32.069***	18.103***
	(9.174)	(7.890)	(7.013)	(8.630)	(6.778)
$t+5$	35.743***	9.352	29.298***	33.766***	19.443**
	(12.883)	(8.933)	(10.005)	(12.072)	(8.320)
$t+6$	38.859***	16.282	32.390***	39.406***	22.045*
	(13.342)	(12.062)	(10.766)	(11.915)	(11.697)
Additional controls:					
Firm-level determinants	Yes	Yes	Yes	Yes	Yes
Firm-FE	Yes	Yes	Yes	Yes	Yes
Country-Year-FE	Yes	Yes	Yes	Yes	Yes
Lagged dep. var	Yes	Yes	Yes	Yes	Yes
R^2	0.20	0.20	0.20	0.22	0.19
Observations	22,727	22,727	22,727	14,107	8,620

Notes: The table presents estimates from regressions explaining firms' debt ratios. The regression is similar to the baseline specification defined in Equation (1) and additionally contains interaction terms of the patent stock variable, a country-specific year indicator equalling one in the respective years (1-6) after the implementation of the Enforcement Directive, denoted as $t + j$ ($\forall j \in [1, 6]$). This interaction term is multiplied with a binary indicator equalling one if the firm from the tech sector (Column I), the non-tech sector (Column II), or no additional interaction is used (Column III). In the last two columns the sample is split according to tech-firms (Column IV) and non-tech firms (Column V). The use of controls is indicated in the bottom of the table. Standard errors (in parentheses below coefficients) are heteroscedasticity-consistent and clustered at the firm level. *, **, and *** denote significance at the 1, 5, and 10 percent level, respectively.

Table A12: Private versus publicly listed firms

Dependent variable:	Debt-ratio					
Firm-type	Private			Publicly listed		
	(I)	(II)	(III)	(IV)	(V)	(VI)
Patent stock (P)	8.663*	1.059	0.987	-1.681	-2.130	-2.725
	(4.999)	(2.600)	(2.676)	(3.773)	(4.472)	(4.526)
P × Tech firm		20.160*	10.726		1.482	-2.074
		(10.531)	(7.403)		(8.173)	(8.195)
P × Post × Tech firm			22.615***			7.468
			(7.648)			(7.618)
Size	1.919***	1.904***	1.515***	0.663	0.666	0.684
	(0.481)	(0.482)	(0.484)	(1.668)	(1.669)	(1.711)
Profitability	-0.993***	-0.993***	-0.956***	-1.433***	-1.435***	-1.526***
	(0.200)	(0.200)	(0.210)	(0.399)	(0.399)	(0.415)
Tangibility	12.230***	12.293***	11.649***	12.957**	12.950**	15.358**
	(1.718)	(1.709)	(1.774)	(6.141)	(6.145)	(6.225)
Cash	-6.157***	-6.167***	-6.133***	-16.644***	-16.642***	-16.678***
	(1.378)	(1.379)	(1.434)	(3.799)	(3.800)	(3.826)
Constant	-4.042	-3.935	-0.416	17.922	17.889	11.975
	(4.474)	(4.472)	(4.639)	(22.746)	(22.767)	(22.944)
Additional controls:						
Firm-FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year-FE	Yes	Yes	Yes	Yes	Yes	Yes
Time trend	No	No	Yes	No	No	Yes
Lagged dep. var	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.20	0.20	0.19	0.20	0.20	0.19
Observations	24,334	24,334	23,325	2,176	2,176	2,084

Notes: The table presents estimates from regressions explaining firms' debt ratios. The regression is based on the baseline specification (Columns I-II and IV-V) as defined above. Further we include the analysis on the effect of the Enforcement Directive in Columns III and VI, respectively. Variables and sample selection are defined as above. The variable *post* is a country-specific indicator, equal to one if the Enforcement Directive passed legislation in the respective country. The regressors *patent stock* and *post* are included by using their one-year lag. Overall, estimations distinguish between two subsamples: private, non-listed firms (Columns I-III) and public, listed firms (Columns IV-VI). The use of controls is indicated in the bottom of the table. Standard errors (in parentheses below coefficients) are heteroscedasticity-consistent and clustered at the firm level. *, **, and *** denote significance at the 1, 5, and 10 percent level, respectively.

Table A13: Plausibility analysis: assessing potential survivorship bias

Dependent variable:	Debt-ratio		
Firms:	All	Survivors	Drop-outs
	(I)	(II)	(III)
Patent stock × Post	24.785***	23.968***	23.138*
	(7.576)	(7.858))	(12.827)
Additional controls:			
Firm-level	Yes	Yes	Yes
Firm-FE	Yes	Yes	Yes
Country-Year-FE	Yes	Yes	Yes
Lagged dep. variable	Yes	Yes	Yes
R^2	0.22	0.24	0.20
Observations	14,107	10,960	3,147

Notes: The table presents estimates from regressions explaining firms' debt ratios. All variables and their use are defined in Table 5. The main regressor of interest is the interaction term of *patent stock* lagged by one year and the dummy for the implementation of the Enforcement Directive (*Post*). After repeating the estimation specified in Equation (2) (Column I), we split the sample according to firms that are obverved in all periods between 2007 and 2012, i.e. which "survive" the Financial Crisis, (Column II) and those that drop out of the sample during that period (Column II). The use of controls is indicated in the bottom of the table. Standard errors (in parentheses below coefficients) are heteroscedasticity-consistent and clustered at the firm level. *, **, and *** denote significance at the 1, 5, and 10 percent level, respectively.

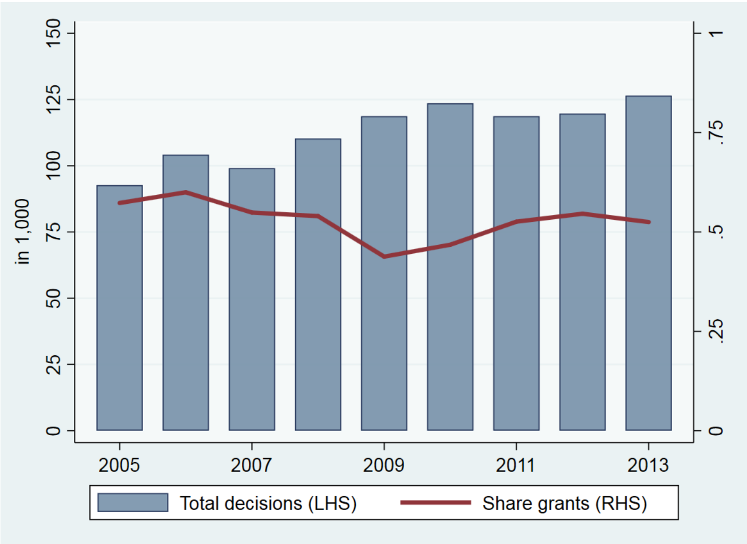
Table A14: Interest burden: tech versus non-tech firms

Dependent variable:	Interest burden			
Sectors:	Tech	Non-tech	All:	
	(I)	(II)	(III)	(IV)
Patent stock (P)	-0.240**	-0.010	-0.083	-0.010
	(0.106)	(0.063)	(0.056)	(0.063)
P × Tech firm				-0.221*
				(0.123)
Size	-0.030***	-0.029**	-0.030***	-0.029***
	(0.009)	(0.011)	(0.007)	(0.007)
Profitability	0.037	-0.002	0.019	0.019
	(0.027)	(0.034)	(0.021)	(0.021)
Tangibility	-0.163***	-0.186***	-0.169***	-0.168***
	(0.040)	(0.048)	(0.030)	(0.030)
Cash	-0.054	-0.147***	-0.090***	-0.088***
	(0.037)	(0.044)	(0.028)	(0.028)
Constant	0.495***	0.525***	0.505***	0.503***
	(0.095)	(0.118)	(0.073)	(0.073)
Additional controls:				
Firm-FE	Yes	Yes	Yes	Yes
Country-Year-FE	Yes	Yes	Yes	Yes
Lagged dep. var	Yes	Yes	Yes	Yes
R^2	0.27	0.22	0.24	0.24
Observations	10,446	5,875	16,318	16,318

Notes: The table presents estimates from regressions explaining the costs of obtaining external funding, i.e. the interest burden of a firm. We split the sample in the subgroups according to their industry-specification: Only tech-firms (Column I), non-tech firms (Column II), and the full sample (Columns III-V). This set of regressions, repeats the specification as displayed in Table 8. All regressors are defined analogeously. The use of additional controls is indicated in respective rows below the coefficients. Standard errors (in parentheses below coefficients) are heteroscedasticity-consistent and clustered at the firm level. *, **, and *** denote significance at the 1, 5, and 10 percent level, respectively.

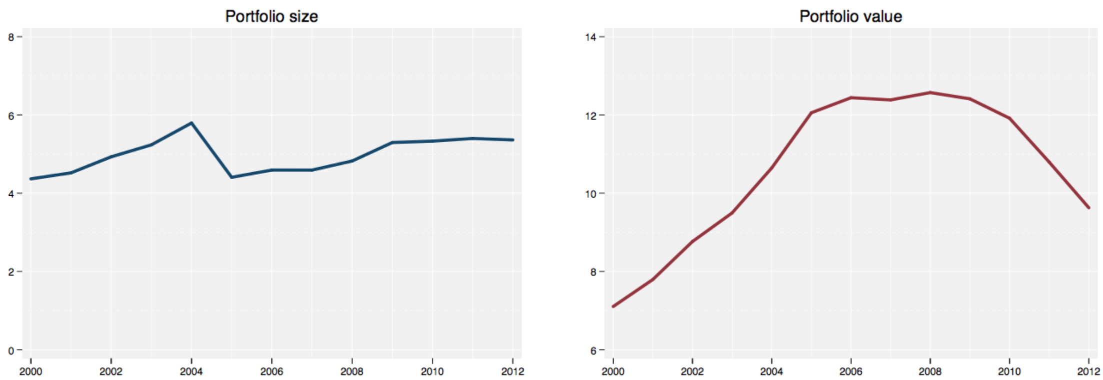
Appendix C: Figures (A1-A3)

Figure A1: Patent decisions and grant rates at EPO (2005-2013)



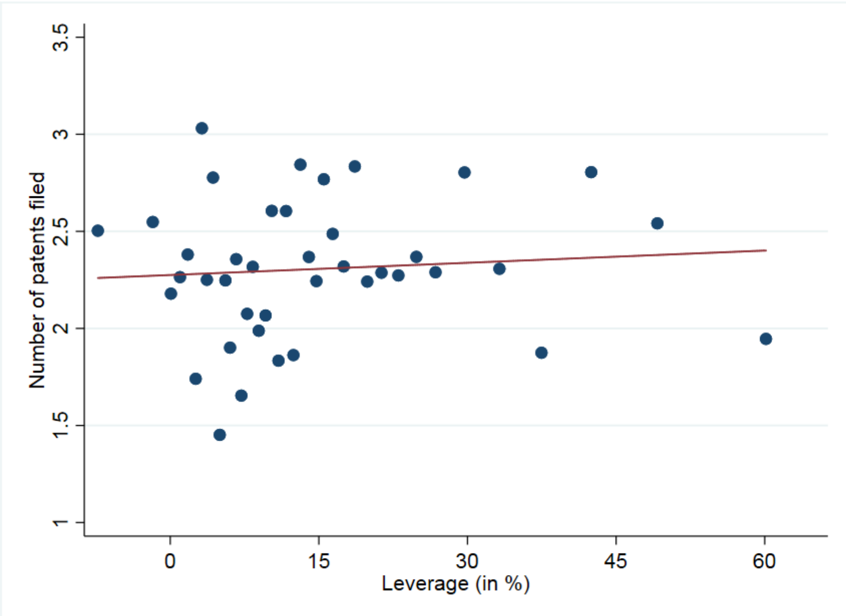
Notes: This figure displays the total number of patent decisions on patent filings, which excludes applications withdrawn prior to publication date at 18 months after filings (indexed on the left-hand side). Further, indexed on the right-hand side, granted patents as a fraction of total decisions are plotted. Note that applications may not be granted due to refusal by EPO as well as deliberate withdrawal prior or during examination. Our graphical illustrations are based on statistics obtained from Harhoff (2016).

Figure A2: Portfolio and family size of sample firms, 2000-2012



Notes: This figures plot the annual means of the (not normalized) patent portfolio size (left) and family size (right) of the full sample ranging throughout the entire sample period of 2000 until 2012. The portfolio size describes the total number of active patents of a firm, whereas the family size counts the number of different patent offices at which these patents are filed. The family size variables represent themselves the average number of patent offices of all patents of a given firm at a given year.

Figure A3: Binned scatterplot: Patent filings and leverage



Notes: This binned scatterplot relates the number of patent filings (y-axis) to leverage ratios (x-axis) for our sample of manufacturing firms and displays the linear fit. The number of bins is set to 40.