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

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Abstract

This paper analyses the importance of one specific type of intellectual property, patents, in determining capital structure decisions. We combine unique institutional features of the European patent system with granular firm- and patent-level data to track the size and value of firms' actively held patent stocks. By exploiting an exogenous shift in patent protection resulting from a change in EU-law, we causally show a positive effect of firms' patenting activities on debt-ratios. Our findings illustrate that this effect is driven by the underlying value of the actively held patent stock and not by the number of active patents or filings. Our setting allows documenting the role of industry, firm, and patent characteristics in this relationship, such as industry's propensity to patent, firms' degree of financial constraints, and the technological scope of patents. The 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, 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). For one specific type of intangibles, patents, anecdotal evidence of both large corporations as well as small and medium-sized enterprises (SME) exists, indicating that its use in loan contracts is more widely spread than literature suggests.[1]

Studying the role of patents is a promising venue to examine the impact of intangible assets on firms' capital structure decision. Firms can potentially use patents both explicitly as collateral and implicitly via signaling future returns. Intangibles gain a certain degree of asset tangibility once they are protected by a patent, because patenting activities are a thoroughly documented, legal construct. This enables potential lenders to assess respective firms' inventive activities, while allowing borrowers to explicitly pledge patents as security. Importantly, however, these type of loan contracts account only for a minor proportion of overall lending. Lian and Ma (2019) show that 80 percent of non-financial firms' debt is based on expected cash flows from operations and not on specific assets. Qua definition, patents help to secure cash flows in the future by granting their owner a temporary monopoly right to appropriate returns. Hence, if firms predominantly borrow against future cash flows, patenting should be a particularly relevant dimension of firms' intangible property to relax borrowing constraints.

In this paper, we investigate the effect of patenting on firms' debt capacity, i.e. leverage ratios. We specifically aim to develop a deeper understanding of the key determinants for this relationship. To address these objectives, we draw on a combination of unique institutional features and highly disaggregate data and show that more valuable patent portfolios causally increase firms' leverage ratios, 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 into a 7.5 percent increase in the average firm's debt to asset ratio. In addition, specific characteristics of the patent portfolio and the patentee affect this relationship. First, the patents' overall stock size and market value are essential complements for determining leverage. Second, we find that the effects are pronounced for firms in sectors with a high propensity to patent, i.e. tech-oriented industries. Third, the relationship of patenting enhancing firms' debt capacity is stronger for firms that are more financially constrained ex ante. Fourth, the technological characteristics of patents in a

[1] For example, the French telecommunication giant Alcatel-Lucent raised 1.6 billion Euro backed by the group's 29,000 patents in 2012 (Reuters 2012). At the same time, a case study by the European Patent Office (EPO 2017) illustrates that using their patenting activities is an important strategy for European SME to draw investors. More broadly, Mann (2018) documents for a sample of patenting firms in the US that 38 percent of them have used their patents for securing debt at least once in their firm history. Finally, even institutional players deploy patents to obtain external funding, such as Yale University which arranged the securitization of the patent for the HIV-drug *Zerit* in the early 2000s (Murphy *et al.* 2012).

portfolio are also relevant for this relationship and affect firms' debt capacity in a non-linear manner. Effects are weakest for both technologically-narrow patent portfolios as well as patents with a very broad technological scope.

In the final step of our analysis, we provide a potential link between firms' patenting activity and their debt capacity. Using the same identification strategy as for the main results, we show that an exogenous increase in patent values leads to lower interest payments. Reflecting a risk adjustment in the prices of loans, loan providers appear to approve larger and more valuable patent stocks as security - even if not explicitly pledged - by offering lower interest rates.

A priori, it is not clear whether patenting enhances firms' debt capacity or whether firms just raise more debt to finance patenting activities. To solve this endogeneity issue, we follow a multilayered approach. We measure the impact of the patent portfolio at the *beginning* of each year on the leverage decision at the *end* of the year which mitigates reverse-causality concerns. Additionally, we explore the staggered implementation of the European Commission's Enforcement Directive (2004/48/EC) across EU member states as an identifying event. This legislative change exogenously increased patent protection during the mid-2000s across all member states but at different points in time by harmonizing and improving enforcement of intellectual property rights (IPR). This allows evaluating the causal impact of an exogenous increase in patenting on financial leverage. Finally, we strengthen our findings with several plausibility tests ruling out that alternative events during our sample period drive results, such as the Financial Crisis or anticipatory effects. Further, we document heterogeneous effects regarding specific characteristics that plausibly enhance ex ante responsiveness to the treatment on an industry-, firm-, and patent level.

Our data set comprises in-depth legal European patent data (PATSTAT) on almost 100,000 individual patents merged with companies balance sheet information (Amadeus) across ten European countries, virtually all industries, and over a time span of 13 years. We combine these comprehensive information with unique institutional features to overcome a second empirical challenge: the precise quantification of intangible property. Early studies try to address measurement issues by focusing exclusively on externally acquired intangible assets, e.g. patents transferred in the process of firm acquisitions or liquidations. In the course of these events, intangible assets become part of the acquirers' balance sheets and are thereby quantified. In contrast, *internally* generated intangibles, are not captured by common accounting practices. However, these are likely to be more relevant, because 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 therefore 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 any given point in time – the patent portfolio. To precisely compute these dimensions, we have to exploit a key feature of the European patent system, the obligatory annual renewal fees. Under this regulatory regime, patent holders have to 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. By tracking these individual payments, we can precisely map the actual size and value of firms' patent portfolios at every point in time. In comparison, in the US patent system, renewal fees are due only three times over the course of 20 years after application.[2]

This approach has several important advantages. By obtaining information on actively held patents, we cover all dimensions of patenting, externally acquired as well as internally generated patents. Furthermore, 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 (Harhoff 2016). 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 (IP5 2018). As another advantage, the high detail of patent data allows us to assess multiple characteristics of the underlying invention. We can therefore paint a nuanced picture of the drivers that link intellectual property to firms' financial leverage.

We extends previous research in multiple ways. 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. Moreover, 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. Next, 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. Finally, our results suggest that enhancing enforcement rules across different jurisdictions benefits innovating firms, which often have difficulties accessing debt funding.

Our study relates to different branches of literature. Most generally, 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 (see e.g. Myers and Majluf (1984), Jensen and Meckling (1976) and Rajan and Zingales (1995)). 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), several papers - such as ours - focus on capital structure determinants across countries, time, or industries (see e.g. Hall *et al.* 2004, Lemmon *et al.* 2008). More explicitly, we contribute to the literature on financial constraints 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.[3] Being particularly

[2] Kogan *et al.* (2017) quantify patent value by the initial stock market reaction after patent publication and thereby assign dollar values to respective patents. This approach is not feasible in our case, because the majority of sample firms are small, private firms which are not publicly traded.

[3] There are several inherent reasons why inventive firms face difficulties in obtaining debt finance. First, debt

exposed to financing constraints are therefore particularly restrictive for these firms and, hence, for their inventive activities. Compared to the rich literature testing for the presence of financing constraints, we focus on inventive activities as a mean for innovation-based firms to eliminate them.

Most notably, our paper relates directly to analyses on the use of intellectual property for obtaining outside funding, in particular debt financing.[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. Our study is not limited to this explicit use but also encloses a complementary effect IPR can have on 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 but not necessarily from pledging them explicitly. Further, in contrast to Mann (2018), our sample is not limited to large, public firms. Large firms commonly have more tangible assets which they might use complementary to their stock of intangibles. Our sample consists of mainly of small firms and it is therefore less likely that the effects of IPR on firms' debt capacity are confounded with regard to a simultaneous use of other assets.

The remainder of the paper is organized as follows. The next section discusses the role of patents in the context of borrowing activities[5] and suggests potential determinants for this relationship by taking theoretical and empirical evidence into consideration. In the third section, we introduce our data set and provide descriptive statistics on our sample. In section four, we present our empirical results, including robustness tests and several extensions. The last section concludes.

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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). 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 on the role of collateral in funding decisions, 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.

2 Institutional background and propositions

2.1 Intellectual property and external funding

Intellectual property rights are designed for their owners to allow appropriation of returns from their investment in intangible assets. Just like tangible property, they may carry inherent value and frequently constitute a substantial part of overall firm value. At the same time, however, only a small fraction of inventions protected by IPR become eventually economically successful. This makes it very hard to predict success or assign market values to IPR ex ante.

As one specific form of IPR, patents are exclusive rights on products or processes that provide new technical solutions to a problem. By law, each patent is fully disclosed after publication making them a valuable source of information for a variety of different parties. Most important for our analysis, this includes but is not limited to (potential) investors and loan providers. Thus, informational asymmetries that impede the prediction of success or market values are less of a concern regarding firms' patented inventions.[6]

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. He stresses that firms holding patent-backed debt performed 49 percent of public-sector R&D investment and 41 percent of patenting activity in the US since 2003 illustrating that this behavior is not limited to a specific subgroup of firms. 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 necessarily tied to a specific, physical asset, but rather based on future cash-flows and, hence, informational content on the borrowers' prospects. Instead, firms borrow today by promising future cash flows. While it is well 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.

More explicitly, 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 by increasing price margings and expansion of sales. Third, due to its purpose of granting temporary

[6] Still, the assessment of patent value is not trivial: 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. For instance, 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).

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 is of strategic importance relieves its owner from paying license fees that would incur if competitors held the patent. Empirical evidence supports these considerations. For example, Farre-Mensa *et al.* (2017) estimate causally that patent grants increase firms' sales growth by, on average, about 80 percent relative to a set of non-patenting 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. The creation of patentable inventions requires effort and a minimum of technological quality and novelty which informs potential lenders about firms' inventive capacity (Conti *et al.* 2013). 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 The relation of patenting and leverage

Following our explanations in the previous subchapter, patenting explicitly and implicitly supports external debt financing either by acting as collateral, by decreasing future cash flow risk, or both. Hence, we expect patenting to relate to firms debt capacity positively, just like other forms of tangible assets.

In order to test for this relationship, 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 newly filed patents is 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 B). Furthermore, only one out of five granted patents is active until reaching the maximum protection of 20 years (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 recapitulate that:

The number of actively held patents reduces agency costs in the borrowing process and thereby leads to higher debt to asset ratios of firms in equilibrium.

Further, we argue 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 propose that only an economically meaningful amount *and* value of assets can mitigate agency problems:

> *The patent portfolio's value is the main driver for reducing these agency costs and thus a higher value leads to higher debt to asset ratios of firms in equilibrium.*

While these considerations provide us with clear predictions of how patenting and financial leverage are correlated, we want to establish a causal link between patenting and firm leverage. We argue that changes in firms' legal environment are a promising venue for exploiting exogenous variation in patent portfolio values. Because patents are a legal construct, their value strongly depends on 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. It follows that the market environment is an important determinant for inventors to appropriate returns on their IPR.

This is reflected in the circumstance that European patents have to be activated in each Contracting State of the European Patent Convention (EPC).[7] 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, whereas Arora and Ceccagnoli (2006) suggest that more effective patents protection enhances the propensity to license patents in the absence of complementary assets. More directly, Aghion *et al.* (2015) show that competition induces firms to increase their R&D intensity only when patent protection is strong. Similarly, Mann (2018) shows that an exogenous strengthening in creditor rights induces firms to increase R&D expenditures. Given these aspects, we expect a positive and causal effect of an exogenous shift in patent portfolio value on firms leverage.

In addition to these general inferences, it appears plausible for the treatment to have heterogeneous effects regarding industry-, firm-, and patent portfolio characteristics. First, we expect a more pronounced effect of strengthened IPR enforcement on firms' capital structure decisions in

[7] 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.

industries with a higher propensity to patent. The perceived and actual possibility to exploiting patents in case of financial distress is one important channel how a more valuable patent portfolio can increase firms' debt capacity. This implies that a higher precision to value the patent is crucial. For example, Loumioti (2012) shows that borrowers' reputation positively affects their ability to deploy intangible assets for attracting loans. In line with this thought, it should be more likely for patenting to attract debt finance, if it is a rather common practice in a firm's economic environment. In contrast, if patenting was not a well-established business strategy, it is more difficult to evaluate the potential value arising from them. Hence, we propose that:

> *The effect of an exogenous increase in patent portfolio value on firms' leverage is strongest for firms in industries with a high propensity to patent.*

Moreover, firm characteristics, especially firms' ability to access funds, should determine whether and how strong firms' leverage increases due to an increase in their patent portfolio value. Specifically, we can expect effects to be more pronounced for firms with relatively limited access to external funding prior to the treatment. For instance, Faulkender and Petersen (2005) suggest that firms with access to bond markets are less likely financially constrained. Further examples could be young and small firms or other firms that are particularly dependent on external funding. Hence, the potential positive effect of a valuable patent portfolio should be disproportionately high for those firms dependent on external funding relative to firms that are able to tap on either internal cash flows or external equity markets. These considerations let us suggest that:

> *The effect of an exogenous increase in patent portfolio value on firms' leverage is strongest for firms with difficulties in accessing funding.*

Finally, in addition to the size and market value of patents, we expect also other patent portfolio characteristics to be crucial for its effect on firms' debt capacity. The ability to redeploy patents in case of default should be one particularly decisive feature, because it is also closely related to the commercial value of a patent. Fischer and Ringler (2014) argue that technology which can be redeployed to practicing entities in similar technological fields in case of default have a particularly high potential to be used in loan contracts. The net present value and, hence, the liquidation value of these patents should be particularly high. We therefore conclude:

> *The redeployability of firms' patent portfolio for subsequent users enhances the effect of an exogenous increase in patent portfolio value on leverage.*

3 Data and empirical approach

3.1 Data sets and descriptive statistics

By combining information from different data sources, 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 observations 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 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). Table A1 (Appendix A) displays the distribution of observations among countries.[9]

Table 1 provides summary statistics on financial and patenting variables of sample firms. To avoid biased estimates from outliers, we truncate variables at the 1^{st} and 99^{th} 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 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. Patenting intensities also vary across industries. Table A2 (Appendix A) displays the distribution of firms across two-digit NACE Rev.2 main categories. The majority of firms (56 percent) are in the manufacturing sectors which comprises the so-called tech sectors according to the Eurostat (2018) definition.[10]

- Insert Table 1 here -

3.2 Measurement strategy

A distinct feature about the European patent system provides the core of our measurement strategy. To fully utilize the information on the quantity and value of firms' patenting activities, we have to track these two dimensions over the entire lifespan of each individual patent. For this purpose, the EPO renewal schedule allows for a unique way of measuring firms patenting. Patentees have to pay filing and administrative fees to activate the protection on their invention. Beginning with the third year after initial patent filing, patentees have to pay renewal fees to perpetuate the respective protection. However, unlike in other jurisdictions, the European regulatory regime requires renewal

[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. We acknowledge that EPO filings are associated with higher patent quality, larger firm size and certain industry agglomerations (Harhoff *et al.* 2018). However, this should not affect our results systematically, because we conduct within-group comparisons and control for time-invariant heterogeneity among firms with fixed effects.

[9]Our original sample includes all EU-15 member states at the onset of the sample period in 2000 but we had to drop five countries due to inconsistent data availability (Austria, Greece, Luxembourg, Portugal, and Spain). With the exception of Italy, our sample resembles the true distribution among European countries fairly well.

[10]See Table A3 in Appendix A for a more elaborate definition of tech sectors.

fees to be paid in every EPC member state *and* in every year for which the protection pertains. 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 determine the actual ownership, coverage, and age of individual patents in every point in time.

In our main empirical estimations, we therefore consider the actual size *and* value of all active patents of a firm, i.e. firms' patent portfolio. By observing the annual renewal payments, we can exactly identify the number of actively held patents for each firm in each year. On top of this, we determine the value of respective portfolios along two dimensions of the renewals which both significantly affect the costs of maintaining the patents.[11] Figure 1 illustrates both the increase in fees over the course of a patent's life depending on the number of jurisdictions at which patents are actively held (left graph) and the share of renewal fees in the overall patenting costs (right graph). The idea is that patent value is a function of firms' willingness to incur these costs.

- Insert Figure 1 here -

Hence, the first component for approximating these costs is the number of jurisdictions at which patents are filed, i.e. the so-called family size of a patent. Because each additional jurisdiction at which a patent is active increases the amount of renewal fees, patenting costs vary substantially depending on the number of designated countries. The second component takes into account that the payment scheme is not symmetrical across patent life. Renewal fees are relatively low during the first years but increase exponentially over time, making the last years of patent life the most expensive ones. This escalating fee structure applies across all EPC jurisdictions. We account for this cost factor by considering the average patent portfolios age for each individual firm in each year. Incorporating these portfolio dimensions, we define our main patent measure as:

$$\text{Patent stock}_{it} = Patents_{it} \times States_{it} \times Age_{it} \quad , \tag{1}$$

where $Patents_{it}$ is the number of active patents of firm i at time t, $States_{it}$ and Age_{it} equal the year-specific average number of jurisdictions and the average age of all patents in a given portfolio (i.e. $act.\ patents_{it}$), respectively.[12] Because of strong industry and cyclical heterogeneity of patenting activities, we normalize patent-specific variables on an industry-year basis.[13] This approach also mitigates concerns regarding strategic patenting behavior, which is correlated with industry- and time-specific characteristics of firms (Lerner and Seru 2017).

[11] Regarding these renewal fees in a European context is promising, because they are significantly higher as compared to other main jurisdictions, like for example the US or Japan. For a visual comparison of international fee structures and magnitudes, see Figure A2 in Appendix B.

[12] Figure A3 in Appendix B displays the evolution of the two dimensions across sample years.

[13] We calculate normalized values, $\tilde{p}$, of any patent variable, p, for firm i in period t by: $\tilde{p}_{it} = min.(p_{it}, Q99\,p_{st})/Q99\,p_{st}$, with $Q99\,p_{st}$ being the 99$^{\text{th}}$ percentile value of variable p in sector s at time t. Hence, to account for outliers we normalize by using the Q99 instead of the actual year-industry specific maximum of the patenting variable. For robustness, we repeat our main findings using non-normalized variable specifications.

Combining both quantitative and qualitative features in the patent measure suggests that asset size and value are important complements for attracting debt. Figure 2 drafts the correlation between the size of firms' patent portfolio and their leverage ratios in a binned scatterplot distinguishing among firms with above and below median patent portfolio values. The linear fit suggests a positive relationship between the patents and leverage only for high value portfolios.[14] This supports our empirical approach to consider quantitative and value relevant dimensions of actively held patents when analyzing the effect of patent portfolios on firms' debt capacity.

- Insert Figure 2 here -

The European 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, it is not possible to make inferences on actively held patents by analyzing validation payments.

To illustrate the importance of different fee schedules in affecting the lifespan of a patent, Figure 3 compares the validation rates of patents filed at EPO and USPTO. As technological progress evolves over time, an invention today may not be meaningful in the future anymore, depreciating the value of a patent. The declining rates generally mirror this depreciation in patent values. In fact, the annual renewal schedule at EPO reflects this notion more drastically and potentially realistically. 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. Presumably, the fact that in the US renewal fees do not have to be paid in the last years leads to this result.

- Insert Figure 3 here -

3.3 Augmenting the capital structure equation – correlation evidence

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. Long-term debt is defined as loans and liabilities with a maturity of more than one year. In additional tests 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 2 defines these capital structure determinants. Following Bertrand *et al.* (2004), standard errors are heteroscedasticity-consistent and clustered at the firm level. Equation (2) specifies the augmented capital structure equation:

$$\text{Debt-ratio}_{it} = \phi_i + \gamma_{ct} + \beta_1 \, \text{Patent stock}_{it-1} + \beta_2 \, CS_{it} + \varepsilon_{it} \quad , \tag{2}$$

[14] 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 A4 in Appendix B).

where ϕ_i and γ_{ct} are firm- and country-year-fixed effects. CS_{it} is a vector of capital structure determinants. Debt-ratio$_{it}$ measures firm i's debt ratio at the end of period t. Patent stock$_{it-1}$ is the regressor of interest as defined in Equation (1) measured at the beginning of the period. Hence, β_1 captures the relationship between patenting and leverage..

- Insert Table 2 here -

Table 3 displays the estimates on the augmented capital structure equation. We obtain consistent and statistically significant coefficients across all specifications regarding the standard capital structure determinants (Column I). Specifically, estimates show a positive 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, empirical approach is able to replicate previous findings consistently.

On top of this and most importantly, the 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 median firm's financial leverage by 7.5 percent. This result provides supportive evidence for our line of argument in section 2. In Column III, we adjust the patent stock measure such that it does not account for the average age of firms' patent portfolios. The correlation coefficient remains positive and sizable but is no longer statistically significant. This is also the case if we use the number of actively held patents, without any value considerations (Column IV). When considering the number of patent *applications*, instead of actively held patents, the coefficient is smallest and again not statistically significant (Column V). Combined with our first descriptive evidence, this shows that filings and mere quantitative measures do not have strong explanatory power for firms' debt capacity. Results support the view that larger patent portfolios can be associated with a higher leverage ratio *conditional* on a high market value.

- Insert Table 3 here -

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 as displayed in Tables A4 and A5 in Appendix A, respectively. 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, estimates are most sizable for the one-year lagged patent stock measure (see Table A6 in Appendix A). This is reasonable for two reasons. The zero estimates for lead and contemporaneous variables mitigate reversed-causality concerns (Columns I-III), whereas the most recent patent stock appears most accurate in explaining leverage (Columns IV-VI).

3.4 Identification strategy

3.4.1 Institutional background: the Enforcement Directive

In Equation (2), 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 of property rights to enhance the value of respective patents (i.e. increasing future expected cash flows) and thereby increasing firms' debt capacity. Everything else equal, exogenous variation in patent protection should therefore causally lead to changes in firms' leverage.

The general objective of the Enforcement Directive is to approximate legislative systems in EU member states so as to ensure high, equivalent and homogeneous 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 A7 in Appendix A summarizes the Articles of the Directive.

Implementing the Enforcement Directive should be relevant both for firms as well as potential investors. From a firm perspective, enhanced protection against copying should increase the fundamental value of a patented invention. 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. Further, also from an investor's perspective, patents become a more valuable asset. 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 of the EU (2017) ascertains that the Directive is an effective tool on a general and conceptual level improving enforcement of IPR. According to Fleissner (2009), the amendments made IPR more resilient against illegal copying and thereby strengthened its role in general.[15] In a multi-country setup, like our analysis, these aspects are particularly crucial. Despite international agreements (e.g. the TRIPS agreement), there is no global patent system. Countries can 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 2019). In line with previous considerations, this is detrimental for the value of patents as a legal construct defining the borders of firms inventive activities. Hence, attempts to reduce fragmentation should have a positive impact on the value of patenting rights.

We consider the Enforcement Directive's implementation as a quasi-natural experimental setup,

[15] Appendix D provides further details on the effects of the Enforcement Directive.

because the legislative change affected the value of firm's patent portfolios exogenously. 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 A8 in Appendix A). 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). Next, 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 rights just to target one specific dimension.

To mitigate endogeneity concerns even further, we measure the implementation in two different ways. The first measure indicates whether the directive is transposed into national legislation of the firms' home country. This is a valid proxy, because firms commonly file their patents in their home country, which is usually also the most important business market at least for small firms like in our sample. An alternative, second specification relies on the fact that firms' are treated because of the location their patent portfolio is active. We presume, it is unlikely that firms designate their patents to specific jurisdictions in anticipation of a potentially beneficiary policy to be implemented in a future point in time. Hence, staggered transpositions in foreign countries are the most conservative approach to model the Enforcement Directive quantifying the exogenous shift in patent protection.

3.4.2 Econometric implementation

This institutional setting enables estimation of the causal effect of increases in the market value of firms' patent portfolio on their capital structure by employing a difference-in-differences (DID) methodology. 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 (3) describes our main specification:

$$\text{Debt-ratio}_{it} = \varphi_i + \delta_{ct} + \alpha_1(\text{Affected}_i \times \text{Post}_{ct}) + \alpha_2\text{Patent stock}_{it-1} + \alpha_3 CS_{it} + u_{it} \ , \qquad (3)$$

where φ_i and δ_{ct} are firm- and country-year fixed effects. CS_{it} is a vector of the capital structure determinants and Debt-ratio$_{it}$ measures the long-term debt ratio of firm i at time t. Patent stock$_{it-1}$ describes the patenting activity of firm i at the beginning of the period. All variables are defined as specified in Equation (2). For the treatment variable, $Post_{ct}$, we use two complementary definitions as discussed in the previous subsection. As a simple measure, we define the treatment variable as a dummy that equals one if the Enforcement Directive is implemented in country c, the home country of firm i, at time t-1 or zero otherwise. In a second definition, we account for the fact that patents are held across various jurisdictions in addition to the home market. We therefore compute a measure ranging between 0 and 1, that equals the fraction of all relevant jurisdictions which have implemented the Enforcement Directive and at which the patent portfolio for each respective firm is active.

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. For strengthening identification, we do not only use cross-country variation in the implementation dates but instead also exploit heterogeneity in the different degrees to which firms are affected within countries. Affected_i, is a binary variable indicating whether we expect a firm to be strongly affected by the treatment or not. As a baseline case, we expect firms with a sizable and valuable patent portfolio to benefit most from the change in law. We categorize firms with an above the median level of the patent stock variable during the pre-treatment (i.e. when $Post_{ct} = 0$) as treated. The coefficient of interest, α_1, estimates the effect of the interaction of Affected_i and $Post_{ct}$, i.e. the average treatment effect capturing the effect of strengthened IPR on financial leverage.

Table 4 provides key characteristics of affected and control firms, i.e. high and low ex ante patentees. It shows that affected firms have on average lower debt-ratios as compared to control firms. Importantly, control firms are smaller, younger, and more profitable than affected firms. It is therefore important in our analysis to strictly account for these potentially confounding factors. Moreover, testing for parallel pre-treatment trends is thus particularly crucial in our setup (see section 4.2.2 for an elaborate assessment of anticipatory and lagged effects).

- Insert Table 4 here -

Furthermore, Table 5 displays the mean values of firm's debt-ratios both before and after the treatment occurs. In line with our estimator strategy, we do not observe a statistically significant difference in means for firms that are not considered to be affected by the treatment. In contrast, firms with an ex ante high value patent stock increase their leverage by 1.5 percentage points (11.8 percent). The difference in means is significant at the one percent level. In addition to this, we test whether this difference is caused by the specific definition of affected versus unaffected firms. We therefore use a broader definition that exclusively relies on the ex ante size of the patent portfolio. In line with our expectation, this adjustment does not affect the results.

- Insert Table 5 here -

4 Empirical results

4.1 The Enforcement Directive, patent portfolios, and firms' leverage

The next part of the empirical analysis estimates the causal effect of firms' patent stock on their debt capacity. We exploit the staggered introduction of the Enforcement Directive marking a positive exogenous shift in the value of firms' patent stock.

- Insert Table 6 here -

Table 6 shows estimates on a set of regressions analogue to the augmented capital structure equation (Column I), including the interaction of the patenting variable specified in Equation (1) with the two alternative treatment variables (Columns II and III). Interacting the country-specific indicator variable on whether the Enforcement Directive passed domestic legislation (Column II), shows that the effect is predominantly driven by patent stock values post treatment. The coefficient on the interaction term is sizable (14.209) and statistically significant. At the same time, the coefficient on the patent variable becomes small and statistically insignificant. This indicates that the implementation of the Enforcement Directive in firms' home countries had a positive effect on the use of valuable patent stocks to enhance firms' debt capacity. Moreover, using the fraction of relevant jurisdictions at which the patent portfolio is active and that implemented the directive provides even stronger results (Column III). The coefficient of the interaction term is highly significant at the one percent level and even larger (20.584). Economically this coefficient suggests that one standard deviation increase in the average firms' patent measure leads to a 6.0 percent increase in leverage comparing pre- to post implementation levels.

In a second step, we utilize heterogeneity in the treatment effect arising from firms' pre-treatment patenting propensity and thereby mitigate endogeneity concerns. Specifically, we estimate our main specification as defined in Equation (3) which differentiates among firms according to their ex ante patent stock. This approach assumes that firms that have a large number of valuable patents ex ante should benefit from the change in law improving the enforcement of respective patents ex post. Confirming this, the DID estimator using the pre-treatment patent stock value as indicator for affectedness is positive and statistically significant at the one percent level. Its magnitude (2.059) indicates a 16.3 percent increase in leverage for the average *affected* firm after treatment. Next, we repeat the same estimation but use an indicator ($Affected$) based on the median-split of ex ante patent stock size. This specification does not take into account the dimension of patent values, i.e. the age and the number of designated jurisdictions. In this specification the coefficient is smaller (1.547) and only holds at the ten percent level.

- Insert Figure 4 here -

To assess the importance of how to proxy patenting activities, Figure 4 plots these DID estimators (first and second row) as well as those on two broader measures of firms patenting activities. All regressions use the same regression specification from Equation (3). Here a firm is considered to be treated if it holds at least one patent (third row) or filed at least one patent (fourth row) during the year preceding the first implementation of the Enforcement Directive in any relevant jurisdiction for the respective firm. The coefficients are much smaller as compared to the other specifications and in the case of patent filings it is statistically not different from zero.

All observations provide strong evidence in support of our presumptions that patenting has a positive, causal effect on firms' debt capacity. 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. Further, the size and value of patent stocks are important complements in this relationship. Not surprisingly, patent filings cannot explain leverage in a similar manner than the stock of actively held patents.

4.2 Validation of empirical results

4.2.1 Testing alternative mechanisms

(i) Announcement effect

One 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 at the time of announcement 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 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 and published on April 29th, 2004, by the European Parliament and the Council, and zero otherwise. 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. Following our dual approach from the main regressions, we test the effect of the announcement of the Enforcement Directive both on the patent stock variable and on the treatment group, i.e. firms with high ex ante patenting intensities.

- Insert Table 7 here -

Table 7 displays estimations across different specifications both for the continuous patenting variable (Columns I-III) and for the specifications using indicators on the expected affectedness by the treatment (Columns IV-V). Unlike in the baseline scenario all 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. Overall, this test suggests that there is no announcement effect and thus supports the design of our empirical strategy.

(ii) Financial crisis effects

The sample time frame comprises the years of the financial crisis which could be another alternative mechanism that drives our results. The financial crisis had lasting impacts on financial markets and lending behavior across the entire globe. While the Enforcement Directive was transposed in most European jurisdiction during the years preceding the crisis, a potential explanation for our results could be that patenting firms were systematically different affected by the crisis. For example, the inventive activity could be related to the financial health of respective companies. Firms with high patenting intensities during the mid-2000s could have therefore benefited from the financial crisis because patents helped signaling strength. Hence, it would not have been the strengthened patent protection but rather some other mechanism that leads to higher leverage ratios of respective firms.

Because of the proximity in the timing of the two events, entirely disentangling the two is non-trivial. However, if the adverse events in financial markets during the late 2000s are indeed the main driver of results, using the financial crisis as the treatment should lead to more pronounced - or at least similar - effects relative to our treatment measure. We test whether this is case in multiple ways.

- Insert Table 8 here -

In the most simple approach, we exchange the treatment variable with a country-specific dummy that is equal to one if the home country of a firm is in a recession. This way we estimate whether the effect in the treatment only occurs with the onset of the crisis. We use the definition of the financial crisis following Laeven and Valencia (2013). According to the authors, countries faced the crisis once real GDP growth is negative and unemployment rates increase for at least two consecutive quarters and vice versa. Table 8 displays regression results from the baseline specifications (Columns I-III) and those using the crisis as a treatment dummy (Columns IV-VI). Compared to the baseline scenario, the coefficients are positive and maintain the same pattern as in previous regressions, i.e. effects diminish when using only quantity-based patenting measures. Because the timing of the treatment and the financial crisis overlap, it is generally plausible to obtain these positive coefficients. The magnitude and statistical significance of respective coefficients is yet substantially smaller. Hence, using the financial crisis as an alternative treatment does not provide similar results compared to our setup which further strengthens our empirical approach.[16]

(iii) Survivorship effects: post-crisis effects

In the previous exercises we cannot confirm that lending behavior of our treatment group was similarly affected by the crisis as compared to the implementation of the Enforcement Directive. However, these tests only partially rule out the alternative explanation that our results from the main specification are indeed arising from the crisis. Essentially, effects might as well be driven from the period of recovery, i.e. the post-crisis period. As another plausibility check, we therefore test the extent to which survivorship drives our results. 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.

We do not know why firms leave the database and hence we cannot estimate effects on firms that default. Still, we observe about 80 percent of firms during the entire time frame between 2007 and 2012. Thus, we know that these firms survived the crisis with certainty. If survivors (or drop-outs) drive the results, we would expect more (respectively less) pronounced effects if we

[16] In addition to this, we use an alternative specification in which we truncate the sample by the country-specific end of the financial crisis. Table A9 in Appendix A displays regression results, which are in line with the original specification in this subsection.

re-run estimation based on the subsample of surviving firms as compared to estimates on the full sample. We therefore repeat the main regression on the effect of the directive both for firms that are observed in every year between 2007 and 2012.

- Insert Figure 5 here -

Figure 5 displays the results of this exercise graphically. Coefficients on the DID estimators are virtually equivalent across multiple specifications of our baseline setup. We therefore cannot confirm that results are particularly pronounced for firms that survived the financial crisis. Concluded, this analysis provides supportive evidence that results are not driven by post-crisis events. Particularly in combination with the previous findings, we show in multiple ways that our main results are unlikely driven by alternative factors arising from the financial crisis.

4.2.2 Difference in Difference prerequisites

(i) Anticipatory effects and parallel trends

In the following subsection, we test for the robustness of our main findings. The key identifying assumption in our setup is that leverage trends during the pre-treatment period are the same for both firms with ex ante high patent stock values and those without, i.e. affected and control groups. Thus, firms have to follow a common path in the absence of the treatment, while differing in its presence. This is particularly crucial because affected and control 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. Following Granger (1969), 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 is considered to be affected or not as defined in Equation (3).

If firms move along similar paths, estimates on these interactions should not be statistically significant from zero during the pre-treatment period. Figure 6 graphically displays the correlation coefficients and the corresponding 95 percent confidence intervals of the interactions using the regression setup from Equation (3), which controls for other capital structure determinants and country-year fixed-effects. 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 affected and control firms seem to move along parallel trends regarding their leverage decisions during the pre-treatment period.

- Insert Figure 6 here -

In addition to this, Table A10 in Appendix A provides further tests on the prevalence of anticipatory effects by repeating the underlying regression of Figure 6 according to different model specifications. None of the estimates points towards a statistically significant different trend between affected and control group firms' leverage ratios before the treatment. Thus, we do not find evidence that leads us to reject the identifying assumption of parallel trends between ex ante high and low patenting firms.

For precautionary reasons, we test for the necessary condition of the parallel trend assumption in an additional way. Estimates displayed in Table A11 (Appendix A) contain a time trend variable, 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.[17]

In empirical analyses, the parallel trend assumption can never be fully approved, but their absence can be rejected. Applying three different methodologies and using multiple specifications of these tests, we were not able to reject that affected and control firms move along a common path prior to the treatment. Results thus provide strong evidence supporting the parallel trend assumption and the validity of our econometric strategy.

(ii) 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 7 first presents graphical results of this analysis by plotting the interaction of year dummies with the indicator on whether a firm is categorized as affected by the treatment or not. Reconfirming our previous results, estimates on correlation coefficients in the pre-treatment period are low and are statistically insignificant. This is true for firms disregarding their ex ante patenting intensity. Moreover, in the post-treatment phase, we observe a different picture. On the one hand, all estimates on the affected firms' coefficients become positive, increasing over time and statistically significantly significant (at the one percent level from t+2 onward). In contrast, for the group of control firms there no effect during the treatment period, that is estimates are statistically not different from zero throughout the entire time frame. Thus, the paths of treated and control groups clearly diverge after the treatment occurs while moving in parallel before. The graphical analysis further 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.

- Insert Figures 7 here -

Further, we investigate the lag structure of the Enforcement Directive's effect on leverage by means of repeated regression analyses using different categorizations of treatment and control groups. Results displayed in Table A12 (Appendix A) illustrates the time structure of the treatment impact and differentiates among three definitions of the categorization. Column I displays results equivalent to the ones from Figure 7. In the other two specifications, firms are considered as treated

[17] In unreported regressions, we further include country-year fixed effects which does not change the results.

based on a median split of ex ante patent stock size (Column II) or whether they patented before the treatment at all (Column III), respectively. For these two categories, no effect can be observed in any of the first three periods post-treatment. Coefficients only turn large and significant in the period $t + 4$. Because of the large timespan between the effect and the treatment, it may not be feasible to regard this as a plausible result. This is in line with our previous results on the main specification.

4.3 Heterogeneity across industry-, firm-, and patent characteristics

4.3.1 Industry characteristics: tech versus non-tech firms

Another important way to analyze the effects of patenting on leverage is to explore the full depth of our dataset. Several characteristics on industry-, firm-, or patent level may increase the degree to which firms might be able to use their patenting activities for enhancing their debt capacity. Essentially, we expect that the effects of patenting on leverage depend on factors that lie outside the scope of patent portfolio value.

As a first extension of our main results, 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. Our first results suggest that information on quantity and quality of firms' patent portfolios are known at least to a certain degree. Hence, patenting should attract debt finance particularly in sectors in which it is a well-established business strategy.

In this context, we find that industries associated with high patenting propensities are manufacturing sectors, i.e. tech-oriented industries. 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.

Descriptive statistics displayed in Table 9 provide first evidence on differences in patenting and lending activities between tech- and non-tech firms. 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. In line with our previous proposition, these values mirror the notion of high patenting propensity of tech-firms relative to firms from non-tech sectors.

- Insert Table 9 here -

To test whether effects are more pronounced in patenting intensive sectors, Table 10 displays a set of repeated regression estimations. We split the sample according to whether firms belong to the tech sectors as classified by Eurostat (2018) (Columns I-III) or not (Columns (IV-VI). For tech firms, the coefficients of interest are large and statistically significant across specifications, while we do not find effects in the case of non-tech firms.[18] Our findings therefore confirm observations from previous literature and provide further ground for the validity of our overall results. Hence, results confirm that the positive effect of patenting on firms' debt capacity predominantly applies to firms located in industries with high patenting propensity.

- Insert Table 10 here -

4.3.2 Firm characteristics: financing constraints

In addition to this, it is reasonable to expect heterogeneous effects arising from firm-level characteristics. Specifically, we expect effects to be particularly pronounced for firms that are relatively more constrained in their access to funding. Because literature shows that there is not an unambiguous method of quantifying financing constraints (e.g. Farre-Mensa and Ljungqvist 2016), we investigate this aspect along multiple dimensions.

As an initial approach, we draw on the intuition that public firms have a broader set of funding sources available, such as access to capital and bond markets. In accordance to Faulkender and Petersen (2005), we suggest that firms with access to bond markets, i.e. publicly listed firms in our setting, are less likely financially constrained.[19] 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). Following these arguments, the positive effects of patent portfolios on firms' debt capacity should be disproportionately high for relatively less mature, private companies. In contrast, the use of patent stocks for enhancing debt capacity should play only a subordinate role for listed firms. We test this by re-estimating the above regressions splitting the sample according to private and publicly-listed firms.

Regressions displayed in Table A13 (Appendix A) show that only for private firms, the coefficients of interest are large in size, highly significant, and hold across multiple specifications. In stark contrast, for publicly listed firms coefficients are not only much small but also lack statistical significance. Hence, results thus suggest that public firms are less relevant for explaining the baseline results. One potential way to interpret this is that firms lacking access to public markets (and thus being rather dependent on external funding) have a higher propensity to use patents in order to attract debt financing.

As an alternative method to quantify firms' degree of financial constraints, we use two common approximations established in the literature. Often, firm-level constraint indices rely on information that are only available for large public firms, such as bond market ratings or dividend payouts.

[18] The standard capital structure determinants (not displayed) are stable across these industries. This suggests that variation on patent variables is not driven by specific differences among these subsamples. 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 Tables A4-A6 in Appendix A.

[19] For example, bank debt ratios for private firms are higher (15.3) than those of listed firms (14.6) in our sample. In this context, it is important to note that large public firms are oftentimes responsible for a large fraction of overall patenting activities. 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.

Because our sample consists of mainly small and medium-sized firms, we cannot use several of these measures.

The first measure we use to determine firms' degree of financing constraints is the RZ-score as introduced by Rajan and Zingales (1998). It measures the degree of dependence on external funding sources and is quantified by the relation of capital expenditures ($Capex$) to firms' cash flow (CF), specifically: $(Capex - CF)/CF$. Higher values imply that firms are less likely to internally cover their investments in fixed assets and therefore are expected to be relatively more in need of external finance. Unfortunately, our data lacks information on capital expenditures for about 65 percent of observations. Because we do not want our analysis to suffer from potential selection issues, we additionally use the more generally applicable S&A index proposed by Hadlock and Pierce (2010) as a second measure for financing constraints. The measure suggests that firm size and age are the most reliable (non-linear) predictors for financing constraints. According to the authors, small and young firms are particularly constrained, whereas this restriction sharply vanishes as firms become more mature and grow.

In both cases, we do not consider the precise score for defining whether a firm is more or less financially constrained. Instead we consider the industry-specific distribution of respective score in the year the treatment first occurs.[20] We then classify firms as being financially constrained, if they are above the industry-specific median value and vice versa. Thereby, we mitigate concerns both regarding endogeneity of the constrained classification and the precision of the selected financing constraints measures.

- Insert Table 11 here -

Table 11 displays estimates from regressions explaining firms' debt ratios in our baseline setup. We split the sample according to ex ante financially constrained firms, i.e. whether firms are considered as constrained (Columns I-III) or not (Columns IV-VI). Financing constraints are defined as firms RZ-score (Panel A) or S&A index value (Panel B). In both cases the coefficients of interest are large and statistically significant for the respective subset of constrained firms. These results support the notion that the positive effect of a valuable patent portfolio is disproportionately high for firms that are limited in their access to these sources.

4.3.3 Patent characteristics: specific versus broad patents

In a next step, we test whether underlying characteristics of firms' patent portfolio play a role for firms' ability to secure loan contracts with patents. Patents vary not only in their technological quality and commercial value but also along other dimensions which may be important for their potential role in debt contracts. As discussed in section 2, an important characteristic is the ability to redeploy the patent.

[20] This year is firm-specific, because we consider a firm to be treated once the change in law occurs in one of the designated EPC member states at which a patent in the patent portfolio is active. We take the year of the implementation, because in our baseline estimations, the coefficient of interest (i.e. the interaction term of treatment and treated indicators) is lagged by one period.

We propose the technological scope of patents as a proxy for redeployability. It determines the patent owner's boundaries of the exclusive rights and therefore aspects that can be legally protected and enforced (Zuniga *et al.* 2009). Bresnahan and Trajtenberg (1995) show that the spectrum of related technology classes explains patents' degree of technological novelty. On top of this, Gambardella *et al.* (2007) argue that patent breadth directly relates to the number of potential (subsequent) users and therefore affects revenue inflows, i.e. liquidation value.

A priori, however, it is not clear to predict the direction in which patent breadth determines redeployability. While some scholars argue that broader patents relate to higher anticipated liquidation value (e.g. Gambardella *et al.* 2007) others do not find an effect of patent-specific characteristics, such as the patent scope (e.g. Fischer and Ringler 2014). Given the potentially important role of technology classes a patent portfolio relates to, this ambiguity asks for a thorough analysis, which our highly granular data allows us to investigate.

We quantify 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).[21] In the following, we define pre-treatment portfolios referring to one single technology class as ex ante *specific* (resembling 33.7 percent of all portfolios), whereas all other pre-treatment portfolios are generally defined as ex ante *broad*.

- Insert Table 12 here -

Table 12 contains estimates for our baseline setup augmented splitting the sample according to the pre-treatment portfolio breadth defined by the patent scope. Comparing specific (Columns I-II) and broad (Columns III-IV) portfolios shows that the mere magnitude of the effects do not differ between specifications. This holds for both the single effect of patent portfolios (11.755 and 11.960) and the combined effects ($36.242 - 14.006 = 22.236$ and $17.849 + 5.567 = 23.416$). In terms of statistical power, however, differences are strong. Estimates on firms with ex ante specific portfolios lack precision and suggest higher variance within this group. In contrast, estimates on both the single portfolio regressor (Column III) and its interaction term with the post-treatment indicator (Column IV) are statistically significant at the five percent level.

Despite these differences, these results do not provide conclusive evidence on the relevance of patent portfolios' scope for our main results. We therefore go one step further by splitting the subsample of firms ex ante broad portfolios into equally sized quartiles according to their location

[21] 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 $\tau - 1$, where τ refers to the firms-specific year in which the staggered treatment starts.

in the pre-treatment originality index distribution. Results suggest that portfolios that are located either in the second or third quartile (Q50 or Q75) account for the results. Figure A5 (Appendix B) illustrates the locations of respective firms across the originality index distribution graphically. As opposed to firms located in the first and fourth quartile (Q25 and Q100), coefficients of the interaction terms are much larger (26.955 and 42.067 versus 5.001 and -1.481) and statistically significant. Hence, this more detailed assessment suggests that the relationship between the portfolio scope and its relevance for enhancing firms' debt capacity is non-linear. Results indicate that firms with patent portfolios which are rather broad, but not too broad, use their patenting activities to increase leverage. This notion is in line with the ambiguity in the literature regarding technological scope and patent redeployability discussed above.

4.4 Connecting patenting and leverage: the costs of obtaining debt

4.4.1 Patent portfolios and interest burden

As a final step in our empirical analysis, we establish one potential link between firms' patent portfolios and their leverage ratios. The underlying notion is that both direct as well as indirect use of patenting in the context of loan contracts helps reducing borrowing costs. Improved access to finance by patents' signaling future cash flows should be reflected in respective firms' cost of obtaining external funding. In this subsection, we therefore investigate whether patenting affects the interest expenses of affected firms.

Because of the structure of our data, we do not observe individual loans and, hence, interest rates. However, we are able to measure firms' interest burden as the fraction of interest expenses over the average long-term debt held during the period. We compute this average by calculating the unweighted mean of long-term debt at the beginning and the end of each period. In an alternative specification, we use the logarithm of total interest expenses. Both measures therefore consider all financial charges of a year. Hence, these proxies tend to overestimate the burden that arises from firms' external debt holdings. This measurement issue should lead towards underestimating the effect of patenting on firms' interest rates. Our estimates using the proposed measures can thus be regarded as a conservative approach. Overall, the measure still comprises sufficient informational content to assess whether patenting affects the costs of firms to obtaining external funding.

- Insert Figures 8 here -

We conduct a set of descriptive analyses to provide a general overview on the relation between patenting and the costs of obtaining debt. As first descriptive insights, we take the differences in means of our interest burden measure comparing both firms with high and low ex ante patenting value, i.e. treated and control firms. The average interest burden for treated firms is significantly different at the one percent level comparing pre- (8.83 percent) to post-treatment rates (8.44 percent). At the same time, no significant difference is observed for control firms in respective periods (8.69 versus 8.56 percent).

Second, we draw a binned scatterplot displaying normalized patent stock value (y-axis) and interest burden (x-axis) of both affected and control group firms as well as pre- and post treatment. Figure 8 illustrates that there appears only a shift in the slopes of the linear fit for firms with ex ante high patent portfolio values (left graph). For control firms, respective slopes are flat both before and after the treatment (right graph).

Third, equivalent to Table 3, we test in an augmented capital structure equation setup which patenting dimension relates most strongly to interest burden. Table A14 in Appendix A shows that also in this relationship, the patent stock value is most decisive when explaining borrowing relevant dimension, i.e. here the costs of obtaining debt.

4.4.2 Patent portfolios, the Enforcement Directive and interest burden

All three descriptive approaches point towards a negative correlation between interest burden and patent portfolio value, particularly in the post treatment phase. This potentially suggests a stimulating effect of patenting on the costs of obtaining debt. In a set of repeated regressions, we further tests whether these descriptive insights can be confirmed by multivariate analyses.

Table 13 summarizes the main estimates on the effect of firms' patent portfolios on their interest burden ratios. Intuitively, the coefficients on the standard capital structure determinants are inverted compared to the baseline setup that uses debt ratios as dependent variable.[22] Additionally, we control for a supply side determinant for the costs of obtaining debt, firms' cash flow. By taking its ratio relative to firms' turnover, we proxy whether firms recognize their profits aggressively (which is the case if the ratio is low) signaling risk associated to a borrower.

Equivalent to the analyses in the previous subsection, we repeat estimation from the baseline regression (Table 6 but use both our measure of interest burden (Columns I-III) and an alternative logarithmic specification for robustness (Columns IV-VI). The negative signs of the coefficients support descriptive findings. Most notably, the interaction term of the treatment indicators (Columns III and VI) are statistically significant at the five percent level. Findings are consistent with across specifications but most of the results lack statistical power. This might be due to the imperfect accuracy of our measure or also due the smaller sample size which arises from missing values for the interest expense variable.

- Insert Table 13 here -

We therefore conduct additional analysis to assess whether the underlying mechanism is valid despite these concerns. First, we tests whether we can replicate the same pecking order in terms of the explanatory power of the different patent related measures. In Table A14 (Appendix A) we thus use four different ways to measure patenting activities on the firm-level. Estimations follow the logic of those in Table 3 by separately including patenting measured by firms' patent stocks

[22] The only exception is the cash-to-asset ratio, which has a negative sign also in these regressions. Our interpretation is that higher cash reserves lead on the one hand to a lower demand for bank debt but at the same time might also signal financial strength, i.e. lower risk of default. Because we also control for cash flows, high cash reserves might induce firms to only obtain (generally expensive) bank debt if costs are relatively low.

size, the number of jurisdictions, and the average portfolio age (Column II), the same measure disregarding portfolio age (Column III), only the number of active patents (Column IV), and the number of patent filings (Column V). The results mirror regressions that explain debt-ratios. The value-relevant measures are substantially larger in size (-0.094 and -0.066) as compared to the pure quantity-based measure (-0.030), and the patent filings (-0.001) respectively.

Second, we investigate the effect of patent portfolio values on interest burden by analyzing the entire lag structure in an event window. Figure A6 (Appendix B) plots the coefficients of year dummies relative to the first treatment year of treated (left plot) and control firms (right plot). While there is no evidence for pre-treatment effects on either specification, we observe negative and statistically significant coefficients for firms affected by the treatment beginning with the third year after treatment. This result confirms our identification strategy and further supports our idea that higher patent value leads to decreased costs of obtaining debt.

5 Conclusion

In this paper, we causally show that the value of patent portfolios enhances firms' debt capacity resulting in higher leverage ratios and lower costs of debt funding. We employ a unique data set, matching in-depth legal patent data (PATSTAT) on approximately 100,000 patents with firms' balance sheet information (Amadeus) across several European countries over a time span of 13 years. Combining these data with distinct institutional features of the European patent system provides us with a valuable structure for our empirical analysis. Particularly, the obligatory, annual renewal fees enable us to precisely track the size and value of each individual patent within firms' patent portfolios in every single year.

In an initial step, we replicate common findings on capital structure determinants. Adding different patent measures shows that higher portfolio values positively relate to firms' leverage. Thus, to the best of our knowledge, we are the first analyzing the impact of patent portfolios on capital structure decisions. We further show that the size and value of the actively held patents are important complements for this relationship. In contrast, no such relationship can be established when using mere quantitative measures, such as filings and patent counts.

We use the staggered implementation of the EU's Enforcement Directive as an identifying event, which enhances the fundamental value of patents by strengthening patent protection and enforcement. We show that this event enhanced patent protection and thus patent value exogenously. Differentiating among ex ante high and low patenting firms thus allows us to causally interpret our findings. Several additional tests confirm that our results are not driven by subsequent or preceding events occurring during our sample timeframe. In our differences-in-differences setting, we additionally document heterogeneous treatment effects across industry-, firm-, and patent characteristics. Firms in industries with a higher propensity to patenting as well as financially constrained borrowers stronger react to the exogenous shift. Similarly, we demonstrate heterogeneous effects regarding the technological scope of firms' patent portfolios in determining leverage. In a final step, we investigate one likely mechanism for this relationship by showing that more valuable patent portfolios lead to lower interest burden and thereby enhance firms' debt capacity.

Our results provide valuable implications from both 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 funding source.

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Tables from the main part:

Table 1: Summary statistics: financial and patenting variables

Variable	**Obs.**	**Mean**	**Std. dev.**	**Min.**	**Max.**
Financial variables:					
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
Patent variables:					
Patents filed (p.a.)	51,719	0.426	3.167	0	144
Size patent portfolio	51,719	4.948	37.113	0	2,684
Average renewal rate	6,484	7.005	3.373	0	18
Average number of jurisdictions	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 2. 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 2: Overview capital structure determinants: measurement and predicted impact

Category	**Variable**	**Definition**	**Predicted impact**
Dependent variable:	Debt-ratio	$= \frac{\text{long-term debt}}{\text{total debt} + \text{total equity}}$	.
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)	$= \sum \text{jurisdictions}_{pit}$	.
	portfolio age (PA)*	$= \text{year}_t - \text{filing year}_{pt}$	.
	patent stock	$= FS_{it} \times PS_{it} \times PA_{it}$	positive

Notes: The table displays definitions of all variables included in the baseline model specified in Equation (2), 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 FS and PA is calculated. *only applies if the patent, p, is active in at least one jurisdiction.

Table 3: Augmenting the capital structure equation: patenting and leverage

Dependent variable:	Debt-ratio				
	(I)	(II)	(III)	(IV)	(V)
Patent stock		10.131^{**}			
		(4.811)			
Patent stock (excl. age)			7.915		
			(5.555)		
Stock size				3.266	
				(2.741)	
Patent filings					0.898
					(0.954)
Size	0.964^{*}	0.971^{**}	0.973^{**}	0.970^{**}	0.917^{*}
	(0.494)	(0.494)	(0.494)	(0.494)	(0.495)
Profitability	-12.358^{***}	-12.373^{***}	-12.379^{***}	-12.367^{***}	-12.433^{***}
	(1.494)	(1.495)	(1.495)	(1.494)	(1.499)
Tangibility	14.444^{***}	14.418^{***}	14.438^{***}	14.423^{***}	14.466^{***}
	(2.084)	(2.084)	(2.082)	(2.085)	(2.113)
Cash	-7.457^{***}	-7.498^{***}	-7.472^{***}	-7.467^{***}	-7.451^{***}
	(1.633)	(1.632)	(1.632)	(1.633)	(1.635)
Constant	2.144	1.880	1.884	1.885	2.480
	(4.958)	(4.962)	(4.962)	(4.962)	(4.967)
Additional controls:					
Firm-FE	Yes	Yes	Yes	Yes	Yes
Country-Year-FE	Yes	Yes	Yes	Yes	Yes
R^2	0.07	0.07	0.07	0.07	0.07
Observations	28,458	28,458	28,458	28,458	28,458

Notes: The table presents estimates from regressions explaining firms' debt ratios. We estimate the standard capital structure equation (Column I) using dependent and independent variables as defined in Table 2. Regressions control for unobserved heterogeneity by including firm- and country-year fixed-effects. In Columns II-V we add different patent measures. In Column II, patent stock refers to the size, value and age of firms' patent portfolio, while age is not considered in Column III. Stock size (Column IV) refers only to the number of active patents in firms' portfolios. Patent filings (Column V) 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. Standard errors (in parentheses below coefficients) are heteroscedasticity-consistent and clustered at the firm level. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table 4: Summary statistics: affected versus control firms

Ex ante patent portfolio value	**Mean values** High	**Mean values** Low	**Difference in means**
Debt-ratio	13.405	15.989	-2.584***
Size (log. assets)	10.470	9.600	0.871***
Cash-ratio	8.625	9.022	-0.397*
Profitability	21.318	22.454	-1.136***
Tangibility	9.909	10.891	-0.981***
Age	32.656	28.011	4.644***
Quoted (in %)	9.839	6.406	3.433***
Llt. company (in %)	64.248	67.438	-3.190***
Patent filings	1.246	0.145	1.100***
Large patent stock (in %)	32.264	3.127	29.137***
Patent life (years)	7.511	6.826	0.685***
Active offices (avg.)	12.120	5.334	7.527***
Originality index	0.762	0.801	0.039***

Notes: The table displays summary statistics on a set of capital structure determinants, firm characteristics, and patenting measures. Variables are defined in Table 2. Patenting variables are based on average firm-year observations. 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 column contains the differences in these mean values, where *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table 5: Average debt-ratios: pre- versus post-treatment comparison

Treatment definition		***Before***	***After***	**Difference in means**
(I) Patent stock value	Affected	12.889	14.410	1.521***
	Control	15.995	15.965	-0.030
(II) Patent stock value	Affected	13.057	14.603	1.546***
	Control	15.579	15.543	0.036

Notes: The table presents mean values of affected and control firms both before and after the treatment according to two different definitions. First (I), we define whether a firm is affected by the treatment according to the ex ante patent stock value. Second (II), we consider only the patent stock size before the treatment. In both cases, firms above the median value are classified as affected. Before and after are defined as the firm specific pre- and post-treatment period. Treatment occurs once at least one jurisdiction at which a patent from a firm's patent portfolio is active implements the Enforcement Directive, i.e. once the treatment measure as defined in Section 3.4 departs from zero ($Post > 0$). The last column contains the differences in these mean values, where *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table 6: Baseline regression: capital structure determinants and patenting

Dependent variable:	Debt-ratio				
	(I)	(II)	(III)	(IV)	(V)
Affected × Post				2.059^{***}	1.547^{*}
				(0.741)	(0.868)
Patent stock × Post		14.209^{**}	20.584^{***}		
		(6.213)	(7.212)		
Patent stock	10.131^{**}	4.689	1.365	8.687^{*}	9.453^{**}
	(4.811)	(3.942)	(4.138)	(4.713)	(4.712)
Size	0.971^{**}	0.987^{**}	0.988^{**}	0.988^{**}	0.988^{**}
	(0.494)	(0.494)	(0.494)	(0.493)	(0.495)
Profitability	-12.373^{***}	-12.370^{***}	-12.369^{***}	-12.318^{***}	-12.350^{***}
	(1.495)	(1.494)	(1.494)	(1.496)	(1.495)
Tangibility	14.418^{***}	14.457^{***}	14.506^{***}	14.404^{***}	14.378^{***}
	(2.084)	(2.082)	(2.080)	(2.085)	(2.085)
Cash	-7.498^{***}	-7.482^{***}	-7.447^{***}	-7.473^{***}	-7.455^{***}
	(1.632)	(1.632)	(1.631)	(1.632)	(1.633)
Constant	1.880	1.583	1.503	1.348	1.647
	(4.962)	(4.965)	(4.965)	(4.956)	(4.966)
Additional controls:					
Firm-FE	Yes	Yes	Yes	Yes	Yes
Country-Year-FE	Yes	Yes	Yes	Yes	Yes
R^2	0.07	0.07	0.07	0.07	0.07
Observations	28,458	28,458	28,458	28,458	28,458

Notes: The table presents estimates from regressions explaining firms' debt ratios. We estimate the augmented capital structure equation (Column I) using dependent and independent variables as defined in Table 2, including the first lag of the normalized patent stock variable. Regressions control for unobserved heterogeneity by including firm- and country-year fixed-effects. In Columns II and III we add the patent stock variable interacted with our treatment variables as defined in Section 3.4. Column II uses the indicator whether the Enforcement Directive is implemented in the firms' respective home country as treatment variable. Column III uses the variable measuring the fraction of relevant jurisdictions that implemented the directive. The last two columns contain regressions specified in Equation (3). Column IV use the ex ante patent value intensity as treatment definition, whereas Column IV uses the ex ante patent quantity definition. Single coefficients on the treatment variables (Post) are dropped because of the inclusion of fixed-effects. Standard errors (in parentheses below coefficients) are heteroscedasticity-consistent and clustered at the firm level. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table 7: Plausibility analysis: the announcement effect

Dependent variable:	Debt-ratio				
	(I)	(II)	(III)	(IV)	(V)
Affected × Announcement				0.879	0.747
				(0.669)	(0.766)
Patent stock × Announcement	6.810	4.505	1.352		
	(5.369)	(4.061)	(2.580)		
Patent stock	0.002	2.677	0.196	1.002	1.326
	(4.990)	(4.350)	(2.293)	(4.942)	(4.953)
Additional controls:					
Firm-level	Yes	Yes	Yes	Yes	Yes
Firm-FE	Yes	Yes	Yes	Yes	Yes
Country-Year-FE	Yes	Yes	Yes	Yes	Yes
R^2	0.12	0.12	0.12	0.12	0.12
Observations	15,209	15,209	15,209	15,209	15,209

Notes: The table presents estimates from regressions explaining firms' debt ratios in our *placebo* setup. All variables and regression specifications follow those in the baseline setup. Unlike in the 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 29th, 2004 and zero otherwise. Column I includes the patent stock measure and its interaction with the placebo event. Next, we use the patent stock measure that disregards the portfolio age (Column II) and the patent stock measure that disregards any value relevant aspects, simply measuring the patent stock size (Column III). In the last two columns, we interact the announcement dummy with the indicator variable on whether a firm is treated, i.e. has ex ante high patent stock value (Column IV) or ex ante large patent stock size (Column V). 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 10, 5, and 1 percent level, respectively.

Table 8: Plausibility analysis: Financial crisis as alternative mechanism

Dependent variable:	Debt-ratio					
Treatment event:	Enforcement Directive			Financial Crisis		
	(I)	(II)	(III)	(IV)	(V)	(VI)
Affected × Post		2.059***	1.547*		0.536	-0.251
		(0.741)	(0.868)		(0.525)	(0.616)
Patent stock × Post	20.584***			6.835*		
	(7.212)			(3.900)		
Patent stock	1.365	8.687*	9.453**	7.892*	9.824**	10.224**
	(4.138)	(4.713)	(4.712)	(4.794)	(4.791)	(4.802)
Additional controls:						
Firm-level	Yes	Yes	Yes	Yes	Yes	Yes
Firm-FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year-FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.07	0.07	0.07	0.07	0.07	0.07
Observations	28,458	28,458	28,458	28,458	28,458	28,458

Notes: The table presents estimates from regressions explaining firms' debt ratios in our baseline setup (Columns I-III) and an alternative specification using the financial crisis as an alternative treatment event (Columns IV-VI). The last three specifications therefore use a binary indicator (Post) as a treatment, specifying whether the home country of a firm exhibits a recession as defined by Laeven and Valencia (2013). Columns II and V use the ex ante patent value intensity as treatment definition. Columns III and VI use the ex ante patent quantity definition. Other than this, all variables and regression specifications follow those in the baseline setup. 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 10, 5, and 1 percent level, respectively.

Table 9: 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	17,151	0.605	11,299	0.362	0.243***
Large patent stock	0	1	17,151	0.144	11,299	0.110	0.034***
Patent lifespan (years)	0	20	17,151	6.930	11,299	7.065	-0.136
Active offices (avg.)	0	37	17,151	8.033	11,299	7.693	0.341***
Debt-ratio	0	100	17,151	13.569	11,299	16.355	-2.786***
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 10, 5, and 1 percent level, respectively.

Table 10: Extension: tech versus non-tech firms

Dependent variable:	Debt-ratio					
Sectors:	Tech sectors			Non-tech sectors		
	(I)	(II)	(III)	(IV)	(V)	(VI)
Affected × Post			1.735** (0.882)			2.158 (1.328)
Patent stock × Post		20.308*** (10.733)			10.927 (7.786)	
Patent stock	26.143* (13.368)	8.113 (2.659)	23.366* (13.371)	4.364 (3.879)	0.513 (3.969)	3.536 (3.855)
Additional controls:						
Firm-level	Yes	Yes	Yes	Yes	Yes	Yes
Firm-FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year-FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.07	0.08	0.08	0.07	0.07	0.07
Observations	17,151	17,151	17,151	11,299	11,299	11,299

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 2. We repeat specifications of Columns I, III, and IV in the baseline estimations in Table 6 but split the sample in the subgroups according to their industry-specification: Only tech-firms (Columns I-III) and non-tech firms (Columns IV-VI). Definitions on the industry affiliation are in accordance with Eurostat (2018). All regressions control for firm-level capital structure determinants, firm fixed effects, and country-year fixed effects as 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 10, 5, and 1 percent level, respectively.

Table 11: Firm-level heterogeneity: ex ante financing constraints

Panel A: Financing constraints measured by firms' ex ante dependence on external finance (RZ-score)

Dependent variable:	Debt-ratio					
	Constrained			Unconstrained		
	(I)	(II)	(III)	(IV)	(V)	(VI)
Affected × Post		3.168***	2.371*		1.280	1.364
		(1.152)	(1.437)		(1.417)	(1.405)
Patent stock × Post	30.693**			27.728*		
	(12.101)			(16.571)		
Patent stock	-14.066	-2.665	-5.459	-4.549	7.674	7.203
	(12.713)	(12.437)	(12.611)	(10.614)	(11.234)	(11.222)
R^2	0.11	0.11	0.11	0.09	0.09	0.09
Observations	5,766	5,766	5,766	6,602	6,602	6,602

Panel B: Financing constraints measured by firms' ex ante size and age (S&A-index)

Dependent variable:	Debt-ratio					
	Constrained			Unconstrained		
	(I)	(II)	(III)	(IV)	(V)	(VI)
Treated × Post		3.091***	1.954		0.704	0.985
		(1.151)	(1.202)		(0.991)	(1.278)
Patent stock × Post	24.182**			19.679*		
	(10.439)			(11.116)		
Patent stock	-3.320	7.728	6.751	3.127	10.422	10.290
	(6.555)	(6.841)	(6.965)	(6.139)	(7.514)	(7.473)
R^2	0.06	0.06	0.06	0.09	0.09	0.09
Observations	9,900	9,900	9,900	15,805	15,805	15,805
Additional controls in both Panel A and B:						
Firm-level	Yes	Yes	Yes	Yes	Yes	Yes
Firm-FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year-FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table presents estimates from regressions explaining firms' debt ratios in our baseline setup. We split the sample according to their degree of being financially constrained. Panel A approximates this by the ex ante dependence on external financing, i.e. the RZ score as defined by Rajan and Zingales (1998) measured at the firm-specific year the treatment begins. 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. Higher values reflect higher dependence on external funding. The significantly smaller number of observations compared to the main regressions is explained by the fact that our data set lacks information on capital expenditures for about 65 percent of observations. Panel B approximates financing constraints by the S&A score (Hadlock and Pierce 2010) measured at the firm-specific year the treatment begins. In both panels, we split the sample at the industry-specific (NACE Rev. 2 main categories) medians of the respective scores for determining whether or not a firm is constrained (Columns I-III) or not (Columns IV-VI). Columns II and V use the ex ante patent value intensity as treatment definition. Columns III and VI use the ex ante patent quantity definition. Other than this, all variables and regression specifications follow those in the baseline setup. 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 10, 5, and 1 percent level, respectively.

Table 12: Extension: broad versus specific patent portfolios

Dep. variable:	Debt-ratio							
Patent scope:	Specific		Broad					
	All		All		$Q100$	$Q75$	$Q50$	$Q25$
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
P × Post		36.242		17.849**	5.001	26.955**	42.067*	-1.481
		(27.802)		(8.265)	(17.060)	(13.337)	(24.881)	(5.605)
Patent stock (P)	11.755	-14.006	11.960**	5.567	14.955	-4.985	0.394	8.788*
	(11.609)	(5.992)	(17.179)	(4.903)	(14.075)	(8.488)	(8.063)	(5.281)
Additional controls:								
Firm-level	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.09	0.09	0.07	0.08	0.09	0.13	0.10	0.11
Observations	5,767	5,767	11,330	11,330	2,831	2,826	2,875	2,798

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 2. We repeat specifications of Columns I and III in the baseline estimations in Table 6 but split the sample in the subgroups according to the scope of the pre-treatment patent portfolio: Specific (Columns I-II) and broad patent portfolios (Columns III-VIII). 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. In Columns V-VIII, we further split the sample of firms with a broad pre-treatment portfolio into four equal sized bin reflecting the location in their location in the pre-treatment originality-index distribution of broad patent portfolios. Originality is a concentration index of IPC4 classes and, hence, lower quartiles 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 10, 5, and 1 percent level, respectively.

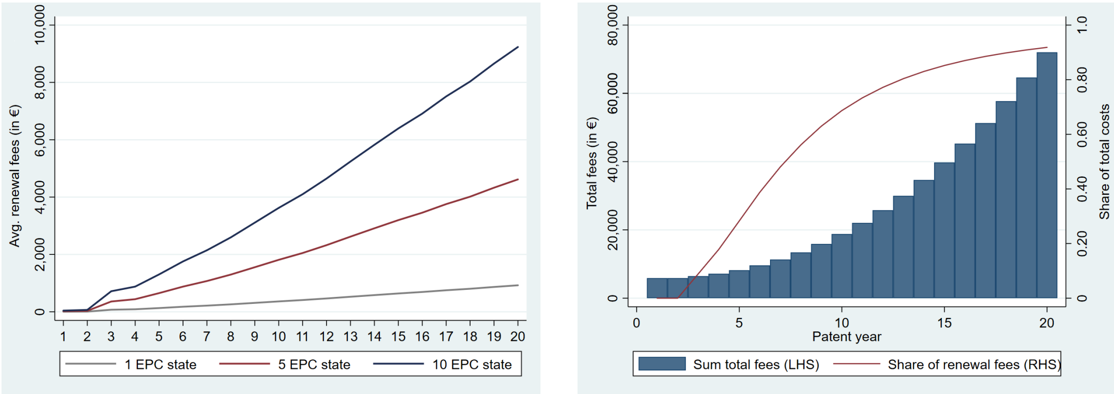
Table 13: The costs of debt: Enforcement Directive, patent stock, and interest burden

Dependent variable:	Interest burden					
Specification:	Interest expenses to avg. debt-ratio			Logarithm		
	(I)	(II)	(III)	(IV)	(V)	(VI)
Affected × Post			-0.023** (0.011)			-0.017** (0.009)
Patent stock × Post		-0.048 (0.113)			-0.040 (0.088)	
Patent stock	-0.097 (0.086)	-0.091 (0.091)	-0.098 (0.086)	-0.066 (0.064)	-0.059 (0.069)	-0.066 (0.064)
Size	-0.001 (0.006)	-0.001 (0.006)	-0.000 (0.006)	-0.000 (0.005)	-0.000 (0.005)	-0.000 (0.005)
Profitability	0.032 (0.019)	0.032* (0.019)	0.032* (0.019)	0.025* (0.015)	0.025* (0.015)	0.025* (0.015)
Tangibility	-0.101*** (0.024)	-0.102*** (0.024)	-0.102*** (0.024)	-0.079*** (0.018)	-0.080*** (0.018)	-0.080*** (0.018)
Cash	-0.099*** (0.024)	-0.100*** (0.024)	-0.100*** (0.024)	-0.080*** (0.018)	-0.080*** (0.018)	-0.080*** (0.018)
CF - Income ratio	-0.033*** (0.012)	-0.033*** (0.012)	-0.033*** (0.012)	-0.025*** (0.009)	-0.026*** (0.009)	-0.026*** (0.009)
Constant	0.224*** (0.061)	0.218*** (0.061)	0.219*** (0.062)	0.188*** (0.047)	0.184*** (0.047)	0.184*** (0.047)
Additional controls:						
Firm-FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year-FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.06	0.06	0.06	0.06	0.06	0.07
Observations	10,104	10,104	10,104	10,104	10,104	10,104

Notes: The table presents estimates from regressions explaining firms' debt ratios. The use of controls as defined in Table 2 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 (3). We sequentially introduce to baseline specification (Column I) as speficied in Equation (2) 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 10, 5, and 1 percent level, respectively.

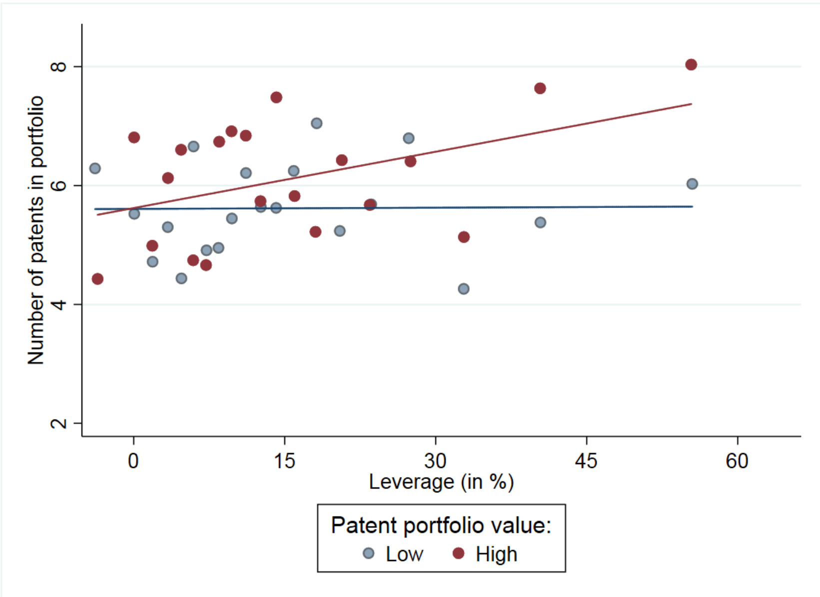
Figures from the main part:

Figure 1: Renewal costs over patent life



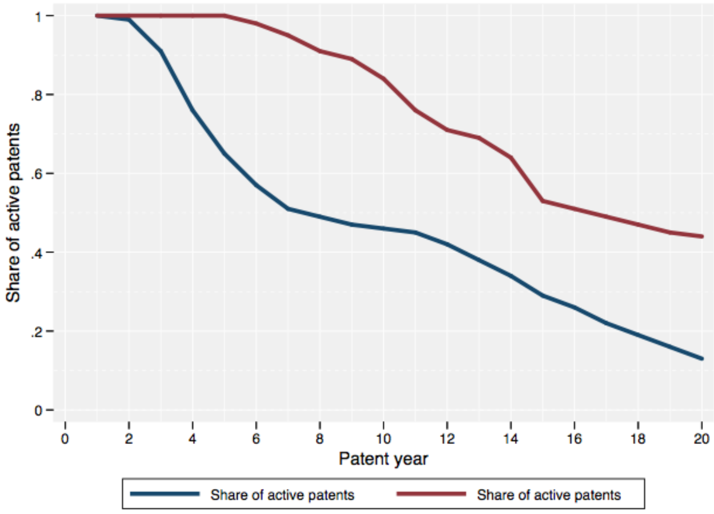
Notes: The two graphs display the renewal structure of patents active in EPC member states over the course of their life span. The left graph displays the average annual renewal fees necessary to maintain patent protection for each of the maximum 20 years of patent life. The lines differentiate among the number of jurisdictions at where the patent is renewed. For illustration purposes this is a linear transformation of the average renewal costs. The costs may actually vary depending on which specific jurisdictions are chosen. The right graph plots the cumulative amount of these average fees over the patent life span (left y-axis) and the share of these costs among total patenting costs (right y-axis). Total patenting costs refers to administrative costs such as translation costs and application costs but does not include costs arising from potential lawsuits. It is assumed that the patent is actively held in 8 jurisdictions which resembles the average number of jurisdictions patents are commonly held in Europe. The reference year for all calculations is the schedule of EPO fees in 2010.

Figure 2: Binned scatterplot: portfolio size and leverage by patent value



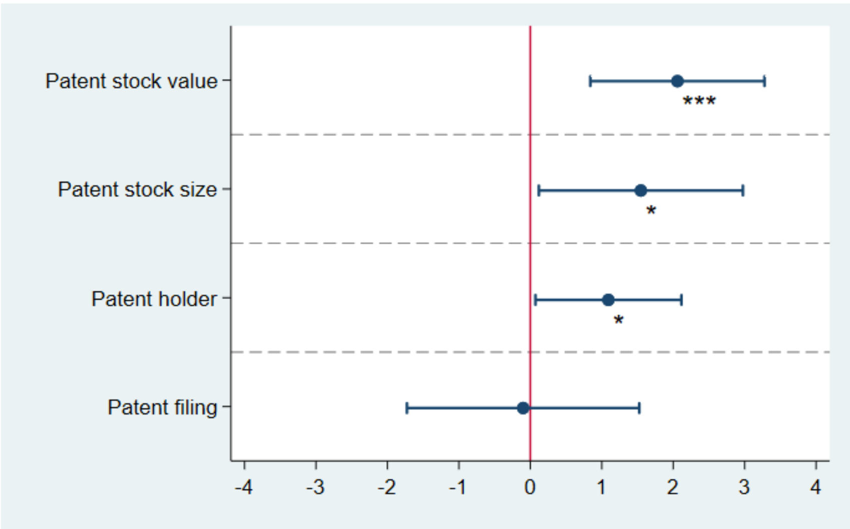
Notes: This binned scatterplot relates the number of actively held patents (y-axis) to leverage ratios (x-axis) for our sample of manufacturing firms. The plot displays the values and the linear fit according to whether firms' patent stock is of high or low value. The value is considered as high, if 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 3: Share of active patents by patent year: EPO versus USPTO



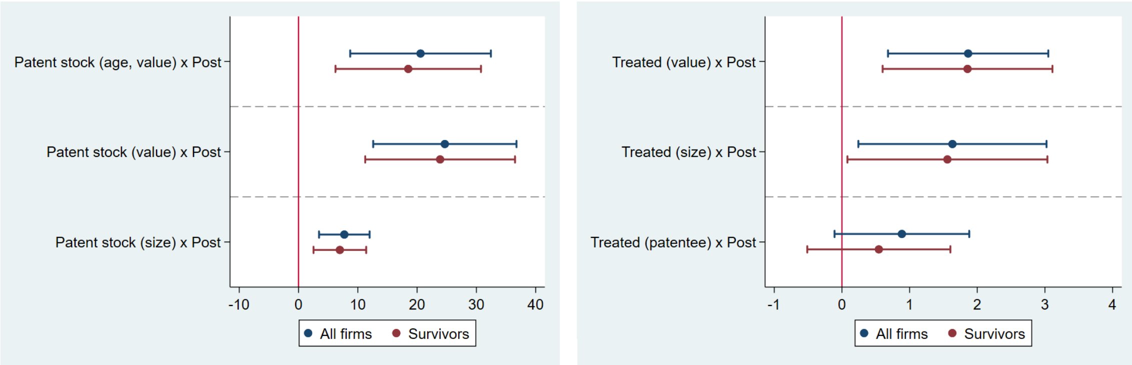
Notes: This figure compares the rate of granted patent registrations existing and in force each patent year starting with the year of application, with a maximum of 20 years. We differentiate among patents filed at EPO and at USPTO, where differing payment fee schedules apply. The EPO shares represent 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 4: Patent portfolio values and leverage: pre- and post treatment comparison



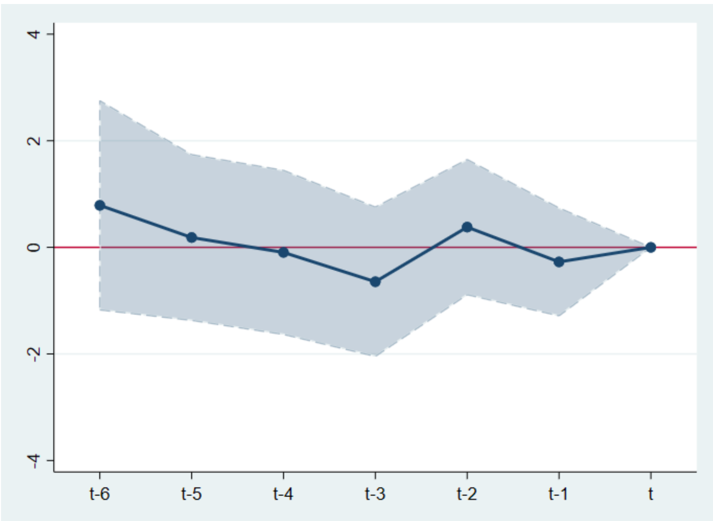
Notes: This figure plots correlation coefficients of the difference in difference estimators obtained from the regression specified by Equation (3). Treatment refers to the share of relevant jurisdictions that implemented the Enforcement Directive. In the first row, we consider firms with an above median patent stock value during the pre-treatment period as affected. In the second row, we make a median split on the size of the portfolio disregarding qualitative aspects. In row three and four, we use a binary variable indicating whether firms held a patent or whether a firm filed at least one patent during the year before the treatment measure departs from its initial value. Whiskers represent the 90 percent confidence intervals. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Figure 5: Coefficient plot: DID estimators on firms surviving the financial crisis



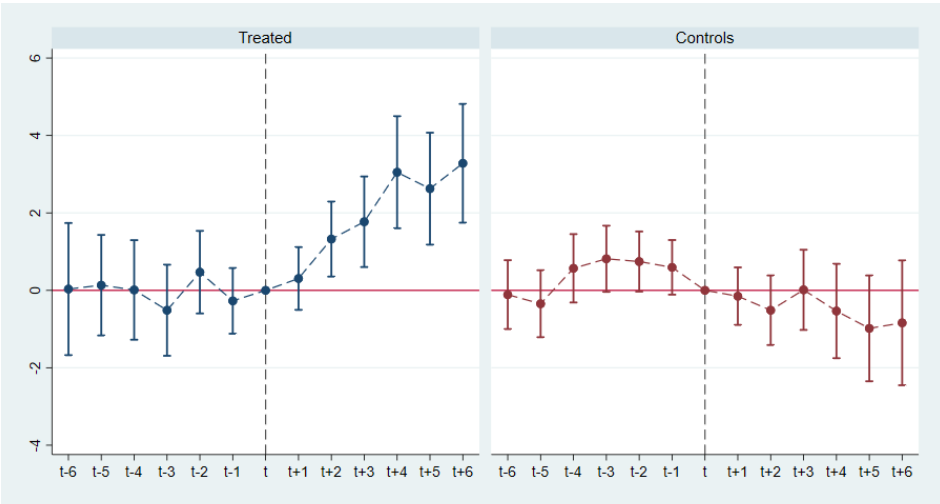
Notes: This figure plots correlation coefficients of the interaction terms of year dummies that indicate the year before the implementation of the Enforcement Directive in the respective country with the binary indicator on whether the firm is in the tech sector or not. These regressors are estimated within in the main specification (Equation 3). Thus, coefficients represent the difference in the paths between tech and non-tech firms in the difference-in-differences setup. The shaded area represents the 95 percent confidence intervals of the estimates. Because we analyze 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 6: Deviation in parallel trends during pre-treatment period



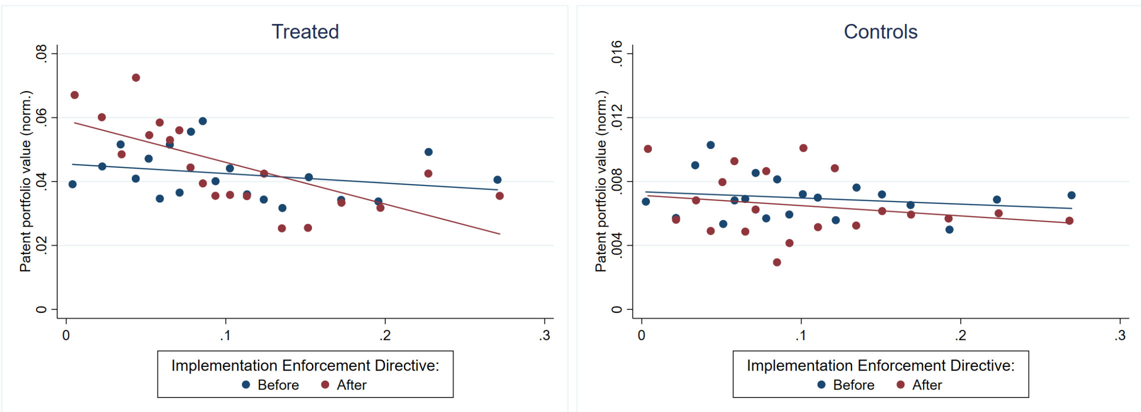
Notes: This figure plots correlation coefficients of the interaction terms of year dummies that indicate the years before the implementation of the Enforcement Directive in the respective country with the dummy indicating whether the firm is considered as an ex ante high patenting firm. These coefficients are estimated within the setup of our main specification from Equation (3). Thus, coefficients capture the difference in the paths between treated and control firms in the difference-in-difference setup during the pre-treatment period. The shaded area represents the 95 percent confidence intervals of the estimates. Because we analyze 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 7: Coefficient plot: portfolio value and leverage across years



Notes: This figure depicts the development of treatment and control groups of patent portfolios on firms' leverage before and after the treatment, i.e. the adoption of the Enforcement Directive. The plot displays the coefficients, $\alpha_{\tau_i}^{Tr}$ (left graph) and $\alpha_{\tau_i}^{C}$ (right graph), of the two individual regressions ($s \in [Tr, C]$): $Leverage_{it} = \vartheta_i + \eta_{ct} + \alpha^s(Firm_i^s \times Enforcement_{t+\tau_i}) + \beta_1 patent\,stock_{it-1} + \beta_2\,CS_{it} + u_{it}$, with $\tau_i \in [-6, 6]$ resembling the year $t + \tau_i$ before/after the first implementation of the Enforcement Directive in any of the jurisdictions relevant for firm i's patent portfolio. $Firm_i^s$ with $s \in [Tr, C]$ is a dummy variable equal to one if firm i has an above median ex ante patent stock value (i.e. for $s = Tr$) or if the firm has a below median ex ante patent stock value (i.e. for $s = N$), that is whether the firm belongs to the treatment or control group, and zero otherwise. The remaining variables are specified as above. Whiskers represent the 90 percent confidence intervals of the estimates.

Figure 8: 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' affectedness to the treatment, i.e. whether they are considered as treated or control firms. Treated (control) firms have an above (below) median ex ante patent stock value. The modified treatment variable is a continuous variable capturing the implementation of the Enforcement Directive in designated EPC member states where individual patents of the portfolio are active. We therefore differentiate among periods in which the Enforcement Directive is not passed in the home country of the firm (*Before*) and those periods when is transposed to domestic legislation (*After*). We exclude all estimated interst rates that are implausibly high, i.e. above 0.2. The number of bins in each subgroup is set to 20. The plot simultaneously controls for capital structure determinants and country-year fixed effects analogue to the baseline specifications in Equation (3).

Appendix A: Tables (A1-A15)

Table A1: 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 A2: 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 A3: 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 A4: Baseline regression using alternative definitions of the dependent variable

Dependent variables:	Alternative leverage proxies							
Variable definitions:	Non-zero borrowers		Raw data		Log. specification		Loan-liability ratio	
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
Affected × Post		1.851**		4.004**		0.186**		0.012
		(0.798)		(1.987)		(0.079)		(0.009)
Patent stock × Post	21.337***		16.656*		1.298**		0.143**	
	(8.247)		(9.802)		0.660)		(0.068)	
Patent stock	1.849	10.376**	4.015	8.301	0.001	0.466	-0.006	0.045
	(4.499)	(5.213)	(5.594)	(5.930)	(0.435)	(0.429)	(0.046)	(0.044)
Additional controls:								
Firm-level determinants	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year-FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.08	0.08	0.08	0.08	0.15	0.15	0.09	0.09
Observations	23,556	23,556	28,458	28,458	21,575	21,575	25,189	25,189

Notes: The table presents estimates regressions repeating the baseline specification corresponding to Columns III and IV of Table 7. In Columns I and II, we restrict the sample to observations with non-zero amount of loans. The remaining specifications use alternative definitions on the dependent variable. The definitions of the dependent variables are the following: non truncated values of the original debt-ratio measure(Columns III and IV), the logarithm of long-term debt (Columns IV and V) and the bank loan to total liability ratio (Column VI and VII). All regressions include firm-level capital structure determinants, firm- and country-year-fixed effects. Variables are defined in Table 2. 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 10, 5, and 1 percent level, respectively.

Table A5: Baseline regression using alternative definitions of the main regressor

Dependent variable:	Debt-ratio					
Patent specification	Value (incl. age)		Value (excl. age)		Size	
	(I)	(II)	(III)	(IV)	(V)	(VI)
Affected × Post		2.168^{***}		2.230^{***}		2.220^{***}
		(0.751)		(0.754)		(0.746)
Patent stock × Post	0.283^{*}		0.432^{**}		0.741^{*}	
	(0.146)		(9.802)		0.384)	
Patent stock	-0.007	0.064	-0.099	0.059	0.001	0.044
	(0.103)	(0.091)	(0.126)	(0.113)	(0.435)	(0.315)
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
R^2	0.07	0.07	0.07	0.07	0.07	0.07
Observations	28,458	28,458	28,458	28,458	28,458	28,458

Notes: The table presents estimates regressions repeating the baseline specification corresponding to Columns III and IV of Table 7. In contrast to the baseline specification, we do not use the normalized values but log-specifications. We vary the definition of the main regressor as follows: patent stock is measured by its size, value, and age (Columns I and II), size and value (Columns III and IV), and only by the number of active patents (Columns V and VI). All patent 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 10, 5, and 1 percent level, respectively.

Table A6: Baseline regression using different lead/lag levels

Dependent variable:	Debt-ratio					
Lead/ lag-level:	Lead			Lag		
	t+2	*t+1*	*t*	*t-1*	*t-2*	*t+3*
	(I)	(II)	(III)	(IV)	(V)	(VI)
Patent stock	3.453	6.481	7.058	10.131^{**}	9.310^{**}	7.910^{*}
	(4.100)	(4.511)	(4.569)	(4.811)	(4.317)	(4.320)
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
R^2	0.07	0.08	0.07	0.07	0.07	0.06
Observations	26,377	29,150	32,123	28,458	24,758	21,525

Notes: The table presents estimates from regressions on firms' debt ratios as specified in Equation (2). All variables are defined in Table 2. Estimates on the control variables are omitted but their use is indicated in the table. In the reference specification (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, t ($\forall\, t \in [-2, 3]$), 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 10, 5, and 1 percent level, respectively.

Table A7: 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, 29$^{\text{th}}$ 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, 29$^{\text{th}}$ 2006.

Table A8: Implementation dates of Enforcement Directive by EU27 member states

Country	**Implementation date**	**Active patents (in % of total)**
Austria	06/2006	3.9
Belgium	**05/2007**	4.2
Bulgaria	01/2007	2.6
Cyprus	07/2006	3.1
Czech Republic	05/2006	2.8
Denmark	**04/2006**	3.7
Estonia	01/2006	2.8
Finland	**04/2006**	3.6
France	**06/2008**	7.2
Germany	**07/2008**	7.9
Greece	04/2011	3.8
Ireland	**04/2006**	3.5
Italy	**04/2006**	6.3
Lithuania	04/2006	2.1
Luxembourg	06/2009	3.5
Latvia	03/2007	1.9
Malta	12/2006	0.9
Netherlands	**05/2007**	4.9
Poland	06/2007	2.4
Portugal	04/2008	3.7
Romania	09/2005	2.6
Slovakia	03/2007	2.8
Slovenia	03/2007	2.6
Spain	06/2006	4.6
Sweden	**04/2009**	4.3
United Kingdom	**04/2006**	7.3

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 transposition dates. Respective dates are hand-collected from *Petillon (2019)*. Sample countries are highlighted in bold letters. The third column displays the fraction of actively held patents that have respective countries as designated jurisdiction. More specifically, because firms hold patents at multiple jurisdictions, the third column displays the fraction of patents-year observations during which patents are actually held in respective countries.

Table A9: Plausibility analysis: Financial crisis and leverage (alternative specification)

Dependent variable:	Debt-ratio					
Treatment event:	Enforcement Directive			Financial Crisis		
	(I)	(II)	(III)	(IV)	(V)	(VI)
Affected × Post		1.499^{*}	0.758		1.351	2.461
		(0.830)	(0.986)		(1.272)	(1.568)
Patent stock × Post	16.577^{**}			5.717		
	(7.236)			(10.023)		
Patent stock	2.771	7.662^{*}	8.378^{**}	8.224^{**}	8.587^{**}	8.654^{**}
	(3.922)	(3.983)	(4.021)	(3.800)	(4.061)	(4.064)
Additional controls:						
Firm-level	Yes	Yes	Yes	Yes	Yes	Yes
Firm-FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year-FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.08	0.07	0.07	0.07	0.07	0.07
Observations	24,919	24,919	24,919	24,919	24,919	24,919

Notes: The table presents estimates from regressions explaining firms' debt ratios in our baseline setup (Columns I-III) and an alternative specification using the financial crisis as an alternative treatment event (Columns IV-VI). The last three specifications therefore use a binary indicator (Post) as a treatment, specifying whether the home country of a firm exhibits a recession as defined by Laeven and Valencia (2013). Columns II and V use the ex ante patent value intensity as treatment definition. Columns III and VI use the ex ante patent quantity definition. Other than this, all variables and regression specifications follow those in the baseline setup. All displayed time-variant regressors are included by using their first lag. Unlike in Table 8, we exclude post-crisis years from the sample. Standard errors (in parentheses below coefficients) are heteroscedasticity-consistent and clustered at the firm level. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table A10: Assessment of anticipatory effects (pre-treatment)

Dependent variable:	Debt-ratio		
Treatment definition	Patent stock value	Patent stock size	Patentee (yes/no)
	(I)	(II)	(III)
$t-6$	0.788	-0.374	-1.112
	(1.001)	(1.366)	(0.534)
$t-5$	0.185	0.682	-0.469
	(0.793)	(0.907)	(0.801)
$t-4$	-0.095	0.094	0.265
	(0.785)	(0.913)	(0.737)
$t-3$	-0.645	-0.619	-0.174
	(0.714)	(0.792)	(0.660)
$t-2$	0.380	0.868	0.616
	(0.647)	(0.752)	(0.572)
$t-1$	-0.273	0.089	0.006
	(0.516)	(0.631)	(0.446)
Additional controls:			
Firm-level determinants	Yes	Yes	Yes
Firm-FE	Yes	Yes	Yes
Country-Year-FE	Yes	Yes	Yes
R^2	0.07	0.07	0.07
Observations	19,529	19,529	19,529

Notes: The table presents estimates from regressions explaining firms' debt ratios. The regression is based on the augmented capital structure specification, Equation (2), and additionally contains interaction terms of different binary variables indicating whether a firm is affected by the treatment or not with with a firm-specific year indicator equal to one in the respective years (1-6) before the first implementation of the Enforcement Directive, denoted as $t - j\ (\forall j \in [1, 6])$. The treatment variable is defined according to whether a firm has ex ante an above median patent stock value (Column I), patent stock size (Column II), or whether the firm holds any patents prior to the treatment (Column III). The sample is truncated by exluding firm-year observations in all years succeeding the implementation year of the Enforcement Directive. Standard errors (in parentheses below coefficients) are heteroscedasticity-consistent and clustered at the firm level. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table A11: Testing for pre-treatment trends

Dependent variables:	Debt-ratio			
	(I)	(II)	(III)	(IV)
Time trend (T)	-0.514***	-0.481***	-0.484***	-0.462***
	(0.189)	(0.190)	(0.190)	(0.192)
$T\times$ Affected (value)		-0.163		
		(0.175)		
$T\times$ Affected (size)			-0.226	
			(0.186)	
$T\times$ Affected (patentee)				-0.129
				(0.162)
Additional controls:				
Firm-level determinants	Yes	Yes	Yes	Yes
Firm-FE	Yes	Yes	Yes	Yes
R^2	0.04	0.04	0.04	0.04
Observations	16,209	16,209	16,209	16,209

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 has ex ante an above median patent stock value (Column II), patent stock size (Column III), or whether the firm holds any patents prior to the treatment (Column IV). All regressions include firm-level capital structure determinants defined in Table 2 and firm-fixed effects. 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 10, 5, and 1 percent level, respectively.

Table A12: Lag structure of the regression estimates (post-treatment)

Dependent variable:	Debt-ratio		
Treatment definition	Patent stock value	Patent stock size	Patentee (yes/no)
	(I)	(II)	(III)
$t+1$	0.446	0.125	0.091
	(0.551)	(0.582)	(0.432)
$t+2$	1.230***	0.132	0.369
	(0.593)	(0.687)	(0.553)
$t+3$	1.548***	0.550	1.032
	(0.707)	(0.779)	(0.660)
$t+4$	3.046***	2.068***	2.311***
	(0.869)	(0.985)	(0.767)
$t+5$	2.614***	2.297***	1.985***
	(0.875)	(1.013)	(0.818)
$t+6$	3.150***	3.469***	2.836***
	(0.912)	(1.097)	(0.896)
Additional controls:			
Firm-level determinants	Yes	Yes	Yes
Firm-FE	Yes	Yes	Yes
Country-Year-FE	Yes	Yes	Yes
R^2	0.07	0.07	0.07
Observations	27,610	27,610	27,610

Notes: The table presents estimates from regressions explaining firms' debt ratios. The regression is based on the augmented capital structure specification, Equation (2), and additionally contains interaction terms of different binary variables indicating whether a firm is affected by the treatment or not with with a firm-specific year indicator equal to one in the respective years (1-6) after the implementation of the Enforcement Directive, denoted as $t+j$ ($\forall j \in [1,6]$). The treatment variable is defined according to whether a firm has ex ante an above median patent stock value (Column I), patent stock size (Column II), or whether the firm holds any patents prior to the treatment (Column III). Standard errors (in parentheses below coefficients) are heteroscedasticity-consistent and clustered at the firm level. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table A13: Private versus publicly listed firms

Dependent variable:	Debt-ratio					
Firm-type	Private			Publicly listed		
	(I)	(II)	(III)	(IV)	(V)	(VI)
Affected × Post			2.073**			1.431
			(0.810)			(1.589)
Patent stock × Post		25.349***			-3.347	
		(8.141)			(6.238)	
Patent stock	11.790**	-0.415	10.036*	3.480	3.981	3.533
	(5.650)	(4.561)	(5.524)	(5.692)	(5.695)	(5.861)
Additional controls:						
Firm-level	Yes	Yes	Yes	Yes	Yes	Yes
Firm-FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year-FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.07	0.07	0.07	0.12	0.12	0.13
Observations	26,265	26,265	26,265	2,193	2,193	2,193

Notes: The table presents estimates from regressions explaining firms' debt ratios. The regression follows the exact same pattern as Table 10. All variables are and model specifications are defined as above, only this time we split the sample according to whether a firm is listed on the stock market (Columns I-III) or not (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 10, 5, and 1 percent level, respectively.

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

Dependent variable:	Interest burden				
	(I)	(II)	(III)	(IV)	(V)
Patent stock		-0.094			
		(0.083)			
Patent stock (excl. age)			-0.066		
			(0.074)		
Stock size				-0.030	
				(0.037)	
Patent filings					-0.001
					(0.013)
Size	0.001	0.001	0.001	0.001	0.001
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Profitability	0.032*	0.032*	0.032*	0.032***	0.032
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Tangibility	-0.101***	-0.100***	-0.100***	-0.101***	-0.101***
	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)
Cash	-0.100***	-0.099***	-0.100***	-0.100***	-0.099***
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
CF - Income ratio	-0.035***	-0.035***	-0.035***	-0.035***	-0.034***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Constant	0.207	0.208	0.209	0.210	0.207
	(0.060)	(0.060)	(0.060)	(0.060)	(0.060)
Additional controls:					
Firm-FE	Yes	Yes	Yes	Yes	Yes
Country-Year-FE	Yes	Yes	Yes	Yes	Yes
R^2	0.06	0.06	0.06	0.06	0.06
Observations	10,162	10,162	10,162	10,162	10,162

Notes: The table presents estimates from regressions explaining firms' interest burden. The setup repeats regressions from Table 3 but uses the ratio of firms interest expenses over the average outstanding long-term debt in a given period, firms' interest burden, as dependent variable. We estimate the standard capital structure equation (Column I) using the independent variables as defined in Table 2. We further add a control variable default risk to control for further costs related confounding factors. Risk is defined as cash flow (CF) to income ratio, i.e. the higher the ratio the lower the risk. In Column II, patent stock refers to the size, value and age of firms' patent portfolio, while age is not considered in Column III. Stock size (Column IV) refers only to the number of active patents in firms' portfolios. Patent filings (Column V) 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. Standard errors (in parentheses below coefficients) are heteroscedasticity-consistent and clustered at the firm level. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

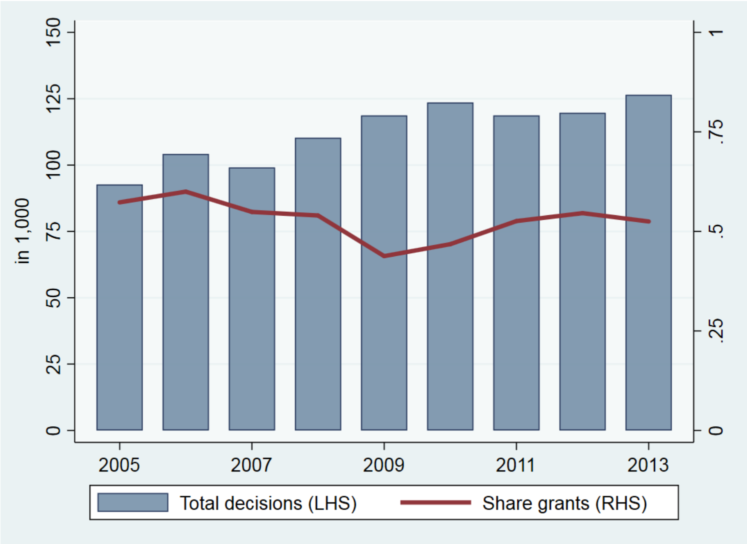
Table A15: Application of injunction in different EU member states (as of 2003)

Member state	**Application rule**
Greece	Generally does not apply on *bona fide* infringers.
Sweden, Finland	Does not apply to individuals acting in good faith.
Denmark, Spain, Italy	Does not apply to individuals who make only private use.
United Kingdom	Instruments for copying can be destroyed if owner knew or had reasons to know that instrument was used for that purpose. Search warrants are lawful (*Anton Piller* order).
Austria, Denmark, Sweden	Search warrants are not unlawful.
Germany	Only instruments that are exclusively used for copying and exclusively owned by the infringer can be seized or destroyed.
France	Freezing injunctions allow the blocking of bank accounts and other assets of infringers (also applies in the UK).

Notes: The table illustrates an example on the fragmentation of IP rights enforcement in the European Union before the Enforcement Directive was implemented. The reference year of these rules is 2003. The subject is the application of injunctions across different member states. The source of this example is the European Commission's COM(2003) 46. For the sake of illustration, we summarized several rules and focus only on a subset applicable in respective member states.

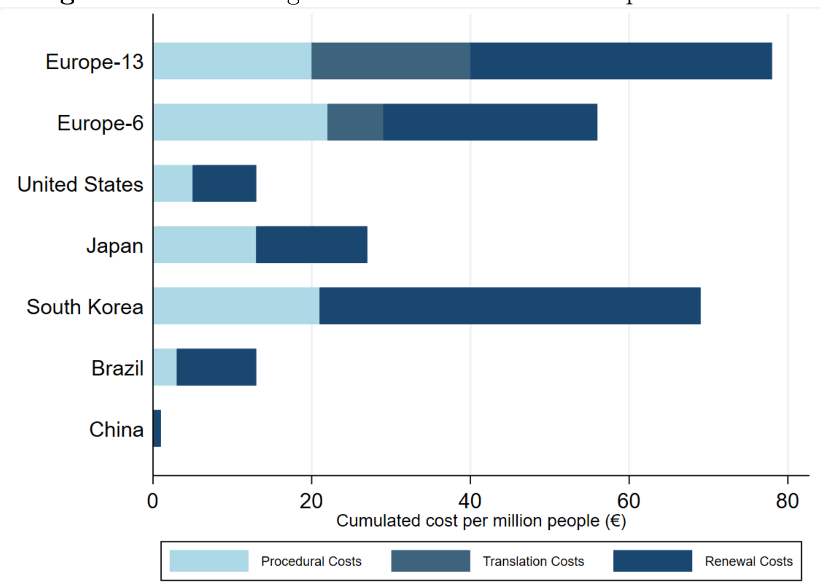
Appendix B: Figures (A1-A6)

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



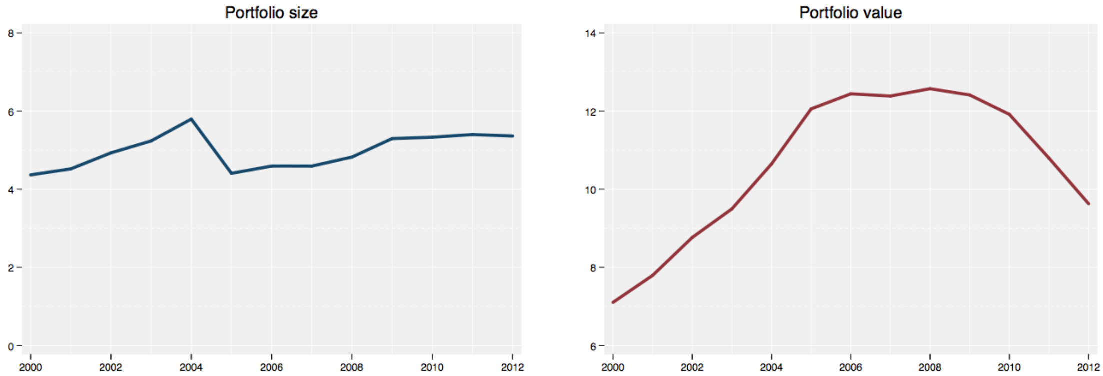
Notes: This figure displays the total number of patent decisions on patent filings, which excludes applications withdrawn prior to publication date at 18 months after filings (indexed on the left-hand side). Further, indexed on the right-hand side, granted patents as a fraction of total decisions are 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: Patenting costs: an international comparison of fees



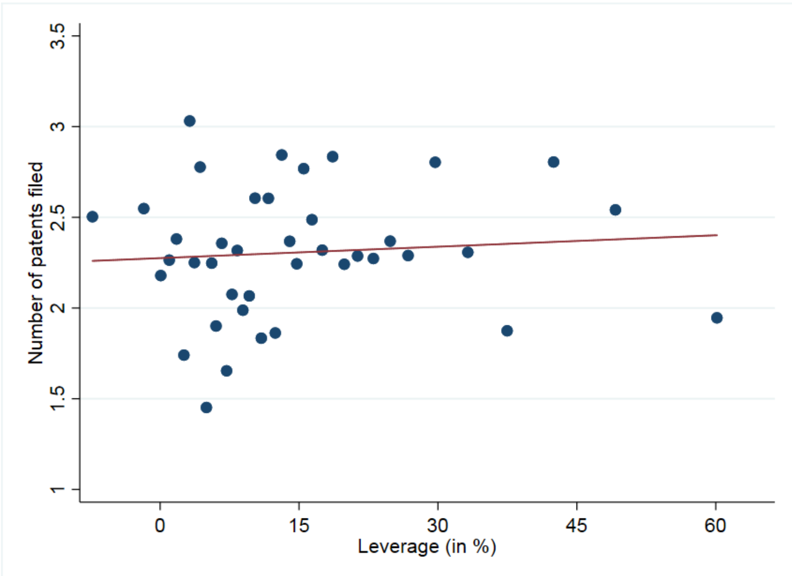
Notes: This graph plots the cumulated costs per million people for the six patenting jurisdictions across the world. Costs are split according to procedural, translation (only applicable in Europe), and renewal fees. Renewal fees in Europe are based on costs applicable before the tenth year of the patent's life and vary depending on the chosen geographical coverage.Europe-13 (-6) refers to a patent active in 13 (6) EPC member states. Own illustration based on Van Pottelsberghe de la Potterie (2010).

Figure A3: Portfolio and family size of sample firms, 2000-2012



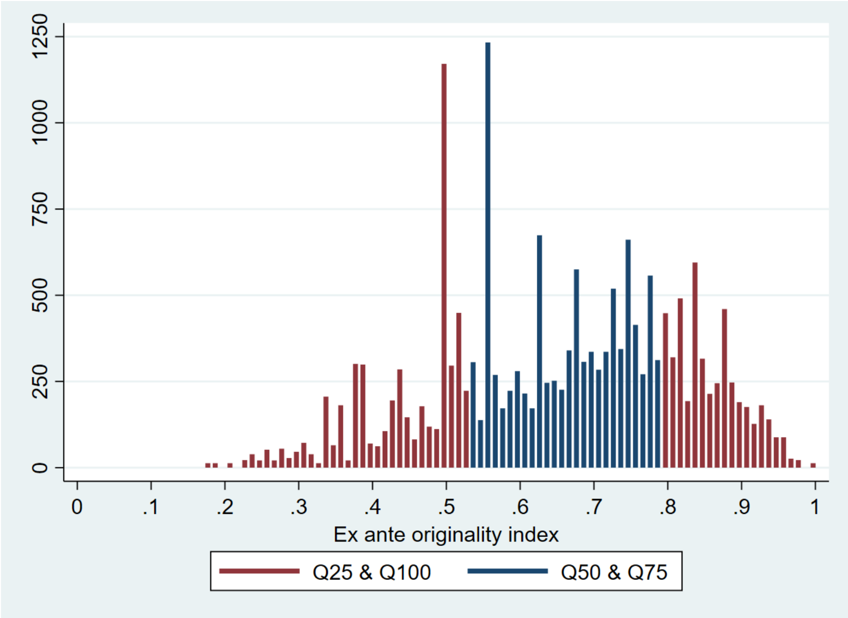
Notes: This figures plot the annual means of the (not normalized) patent portfolio size (left) and family size (right) of the full sample ranging throughout the entire sample period of 2000 until 2012. The portfolio size describes the total number of active patents of a firm, whereas the family size 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 A4: Binned scatterplot: Patent filings and leverage



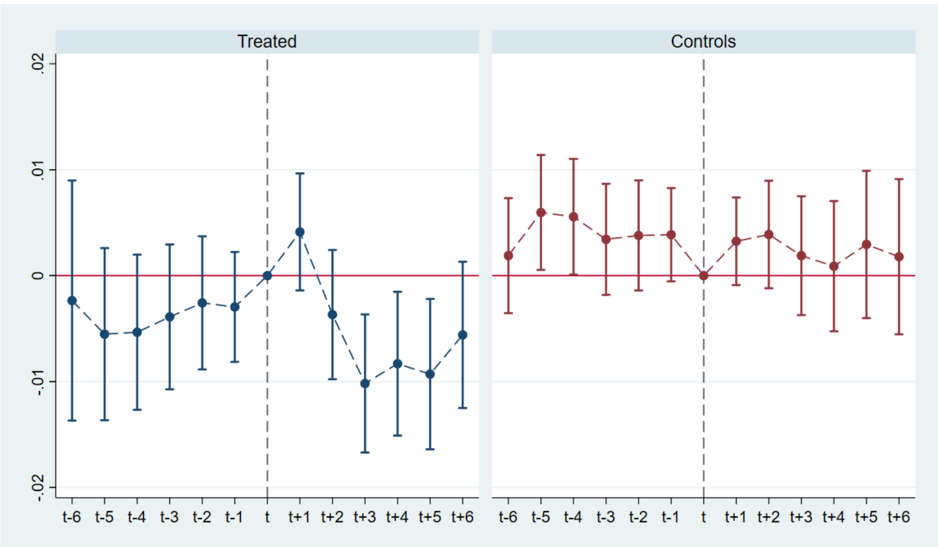
Notes: This binned scatterplot relates the number of patent filings (y-axis) to leverage ratios (x-axis) for our sample of manufacturing firms and displays the linear fit. The number of bins is set to 40.

Figure A5: Pre-treatment originality index distribution



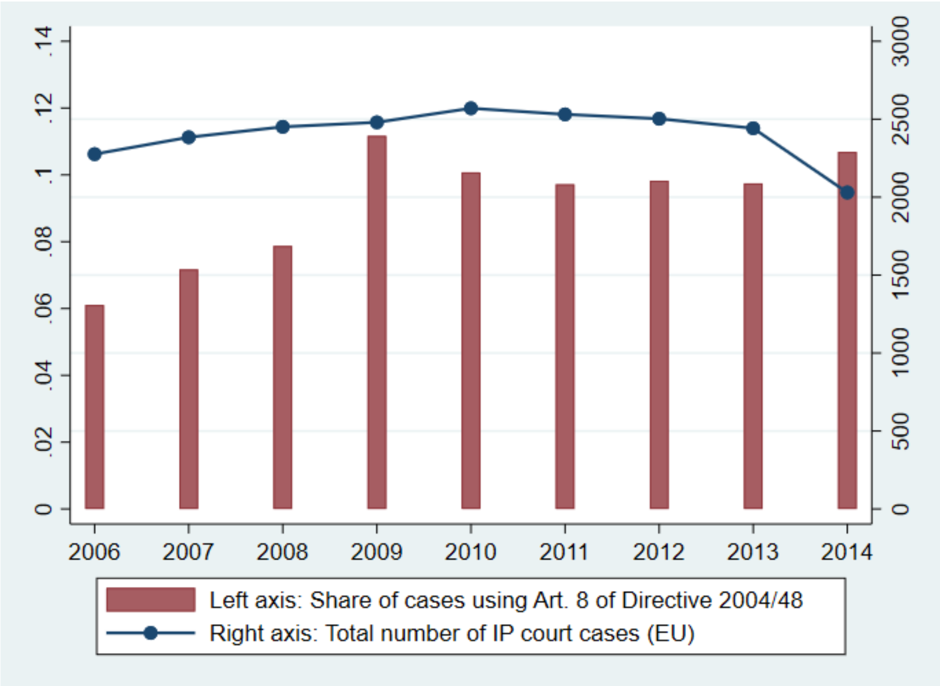
Notes: This histograms displays the distribution of the pre-treatment originality Herfindahl-index of firms' patent portfolios in terms of the absolute frequency of observations (y-axis). Originality is measured based on the number of different technology classes respective patents refer to: $originality_{it} = \sum_{j}^{n_i} bwd_{ij}^2$, 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 $\tau - 1$, where τ refers to the firms-specific year in which the staggered treatment starts. The different colors identify whether an observation lies within the first or fourth quartile (Q25 & Q100) or in the second or third quartile (Q50 & Q75) respectively.

Figure A6: Coefficient plot: portfolio value and interest burden across years



Notes: This figure depicts the development of treatment and control groups of patent portfolios on firms' interest burden before and after the treatment, i.e. the adoption of the Enforcement Directive. The plot displays the coefficients, $\alpha_{\tau_i}^{Tr}$ (left graph) and $\alpha_{\tau_i}^{C}$ (right graph), of the two individual regressions ($s \in [Tr, C]$): $Interest\,burden_{it} = \vartheta_i + \eta_{ct} + \alpha^s(Firm_i^s \times Enforcement_{t+\tau_i}) + \beta_1 patent\,stock_{it-1} + \beta_2\,CS_{it} + u_{it}$, with $\tau_i \in [-6, 6]$ resembling the year $t + \tau_i$ before/after the first implementation of the Enforcement Directive in any of the jurisdictions relevant for firm i's patent portfolio. $Firm_i^s$ with $s \in [Tr, C]$ is a dummy variable equal to one if firm i has an above median ex ante patent stock value (i.e. for $s = Tr$) or if the firm has a below median ex ante patent stock value (i.e. for $s = N$), that is whether the firm belongs to the treatment or control group, and zero otherwise. The remaining variables are specified as above. Whiskers represent the 90 percent confidence intervals of the estimates.

Figure A7: Developments of IP court cases and use of Article 8



Notes: This figure plots the development of the share of total IP court cases in the EU using Article 8, the right of information, of the Enforcement Directive (2004/48/EC). The red bars resemble the shares, which are indicated on the left y-axis. In addition, the blue line draws the total number of IP court cases in the EU and is indexed on the right y-axis. The timeframe spans from 2006, the year in which the majority (>50 percent) of EU member states have implemented the Enforcement Directive until 2014, the most recent for which data is available. Own calculations based on: European Union (2017).

Appendix C:

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).[23]

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.

[23] 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 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 D:

On the effects of the Enforcement Directive (2004/48/EC)

In this subsection we elaborate on the institutional background of the EU's Enforcement Directive. During the early 2000s, a lack of IPR enforcement lead to damages arising from counterfeiting. In fact, in the late 1990s EU firms lost between 400-800 million Euro in the Internal Market due to counterfeiting and piracy (EC 2000). One of the main reasons for this were disparities in legislation leading to significant disparities in the level of protection in the EU. For example, government officials raised worries about market disturbances "*particularly when national differences in the means of enforcing IP rights are exploited*" as stated in the European Commission COM(2000) 789. Another aspect was that existing legislation only provided for enforcement measures on an optional basis. This resulted in disparities regarding the rules for calculation of damages or applying provisional measures and sanctions. Table A15 (Appendix A) exemplifies the fragmentation of IPR enforcement in the case of different national rules regarding the application of injunctions.

These disparities were particularly prevalent in the case of patents. As until today, a European patent is a bundle of national patents, subject to multiple national rules for assessing infringement. While the general purpose of the Enforcement Directive was to approximate the EU's legislative systems for IPR in general, several measures were particularly relevant for patent protection. Among these were the procurement of evidence (stipulated in Articles 6 and 7), the right of information (Art. 8), the prohibition of ongoing infringements through injunctions (Art. 9 and 11), and the specification of damages of the injured party (Art. 13). The general notion was to align measures, procedures, and remedies available for rightholders to defend their IPR in line with best practice.

To illustrate the effect of the change in law, we describe one specific Article in the following. For example, Article 8, the right of information, requires that competent judicial authorities may order that information on the origin and distribution networks of the goods infringing an IPR shall be provided. It is therefore considered a helpful tool to address IP infringements effectively balancing the right of information and the protection of personal data. Figure A7 (Appendix B) displays the actual use of one of the amendments as stipulated in Article 8. The graph illustrates the steep increase in the use of this rule after the adoption of the Enforcement Directive from 6 percent of all IP court cases in the EU to almost 12 percent between 2006 and 2009.

In a more general perspective, an event an evaluation study by the European Union (2017) investigates the implications of the Enforcement Directive. Their findings reveal that the introduction of the Directive does not relate to changes in the number of patent related IPR cases. However, it lead to a substantial decrease in the duration of those cases. This resembles an increase in efficiency of the patent enforcement system. Finally, the study shows that particularly patentees benefited from the change in law. Only 14 percent of respondents answered 'no' to the question whether they believe that the existing rules provided by the Enforcement Directive have helped effectively in protecting IP and preventing IPR infringements.