Borrowing against the (Un)Known: The Value of Patent Portfolios*

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Abstract

We provide new evidence on the importance of intellectual property for external funding decisions by estimating firm-level patent portfolio values in a novel way. Combining unique institutional features with detailed financial and patent data on European firms, we explore exogenous variation in patent protection to show that valuable patent portfolios lead, on average, to about 17% higher debt-to-asset-ratios for a large scale of companies comprising several industries, countries and in particular small and medium-sized firms. Effects are strongest for portfolios with a broad technological scope and financially constrained firms. Hence, intellectual property helps to relax financing constraints of innovative-intense firms.

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1 Introduction

External funding is 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 direct solution to these problems is to provide collateral, which usually takes the form of tangible assets (Shleifer and Vishny 1992, Rampini and Viswanathan 2013). At the same time, it is questionable whether this is an option for borrowers whose firm value predominantly consists of intangible assets or intellectual property (Lev 2000, Harhoff 2011). However, recent evidence shows that intangibles protected by intellectual property rights, such as patents, can help alleviating financing restrictions, despite their inherent opacity and high valuation risk (e.g. Farre-Mensa *et al.* 2020). Anecdotal evidence indicates that the majority of market participants, ranging from large public corporations to small and medium-sized, private enterprises indeed use patents in loan contracts.[1] To the best of our knowledge, besides studies focusing on distinct subsets of firms (e.g. Hochberg *et al.* 2018, Mann 2018), there exists no evidence that patent portfolios affect firms' debt capacity using a comprehensive set of firms.

In this paper, we try to fill this gap by investigating the effect of patenting on firms' debt ratios. We draw on a combination of unique institutional features and highly disaggregated data allowing us to introduce novel and more generally applicable measures of firms' patenting activities. Specifically, we explore annual renewal payments to assess firms' actively held patents. Tracking these payments for each individual patent enables us to estimate expected patent portfolio values on the firm-level. While fee payments are directly informative about the lower bound of expected patent value, we show that our measure is also able to explain the upper part of the value distribution as it positively relates to common measures of technological quality and value, such as patent citations and generality. We can therefore not only shed new light on the impact of intellectual property on firms' leverage decisions but also identify key determinants for the use of patents in debt financing.

For our empirical strategy, we follow a twofold approach. First, we explore plausibly exogenous variation in patent value arising from a major change in EU law. Using a sample of patenting firms and distinguishing among the ex-ante patent portfolio value allows us to deploy a difference-in-differences (DID) setting. Controlling for common capital structure determinants as well as time and firm fixed effects shows that more valuable patent portfolios causally increase firms' leverage. An increase of one standard deviation in the patenting measure translates into an increase in the average treated firm's debt to asset ratio by 17.7%. Moreover, our findings suggest that the size and value of firms' actively held stock of patent are essential complements in this relationship. As a second approach, we match a group of non-patenting firms to our patenting firms which creates comparable treatment and control groups. Reestimating the DID setting using these groups

[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 patenting activities to draw investors is an important strategy for small and medium-sized firms in Europe. More broadly, Mann (2018) documents that 38% of companies from a sample of publicly listed and patenting U.S. corporations used their patents at least once in their firm history for securing debt. 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).

confirms our main results. Heterogeneous treatment effects reveal that specific characteristics of the patent portfolio and the patentee determine the effect of patenting on debt financing. First, we find that the effects are pronounced for firms in sectors with a high propensity to patent, i.e. tech-oriented industries. Second, the positive effect of patenting on the firm-level use of bank debt is particularly strong for firms with limited access to alternative funding sources. Third, the technological characteristics of patents in a portfolio are also relevant for this relationship. Effects are weakest for both technologically-narrow patent portfolios as well as patents with a very broad technological scope. Hence, the effect of technological scope on firms' debt capacity is best described by an inverted u-shape. In the final step of our analysis, we show that an exogenous increase in patent values leads on average to lower interest payments; reflecting a risk adjustment in the prices of loans for larger and more valuable patent stocks.

Studying the role of patents in debt financing is a promising venue to examine the impact of intangible assets on firms' capital structure decision. For example, patents as thoroughly documented, legal constructs provide intangibles with a certain degree of asset tangibility once protection is granted. This enables potential lenders to better assess respective firms' inventive activities, while allowing borrowers to explicitly pledge their property rights as security. Furthermore, by definition, patents help to secure cash flows in the future by awarding their owner with a temporary monopoly right to appropriate returns from the underlying invention. This suggests that patenting can be a particularly relevant dimension of firms' intangible property to draw debt financing.

Studying this entail obvious endogeneity issues. A priori, it is not clear whether patenting enhances firms' debt capacity or whether firms raise more debt to finance patenting activities. To solve this, we follow a multi-layered approach. In all our tests, we measure the impact of the patent portfolio lagged by one year ($t-1$) on the leverage decision one period later (t). This mitigates reverse-causality concerns only partially. We therefore explore the staggered implementation of the European Commission's Enforcement Directive across EU member states as an identifying event isolating the direction of causality. 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 the value of patenting on financial leverage. Moreover, we deploy a Coarsened Exact Matching (CEM) approach which assigns each patenting firm from the main sample to a non-patenting firm. To ensure comparability of the two groups we enforce multiple matching criteria related to observable firm characteristics. Results obtained from this approach are consistent with the main findings. Finally, we strengthen our findings in a series of plausibility tests demonstrating that alternative events during our sample period are unlikely to drive our results, such as the Financial Crisis or anticipatory effects. Specifically, we show that firm size is not able to explain our main results. Further, we document heterogeneous effects regarding specific characteristics that plausibly enhance ex ante responsiveness to the treatment on an industry-, firm-, and patent level.

A second key empirical challenge is the quantification of intangible property. Early studies try to address measurement issues by focusing exclusively on externally acquired intangible assets, such as 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.[2] 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 compute these dimensions, we 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. Payment information directly reflect whether a firm actively holds a given patent or whether it is lapsed. By tracking these individual payments, we can precisely map the actual size of firms' patent portfolios at every point in time.[3]

Furthermore, payment information allow us to proxy the value of the patent portfolios. The repeated investment decision provides a precise estimate on the lower bound of each patent's expected market value. Patenting costs in Europe are economically significant, reaching up to twenty times the costs compared to for example the US (de la Potterie 2010). Further, our approach is also promising since we are able to generate a value measure applicable for a large-scale sample that encompasses the vast majority of the business landscape, particularly a large share of small and medium-sized, private firms. Related studies that estimate specific patent values apply mostly for specific firms, i.e. large public corporations (Kogan *et al.* 2017), or use rather small sample surveys (Giuri *et al.* 2007). Unlike these examples, our estimation approach can assign numbers on the lower bound of firms' patent portfolio values for any firm. In particular, we further demonstrate that our approach is informative along the entire distribution of patent value using common patent quality measure, i.e. patent citations and generality, as proxies.

On top of this, our approach has further important advantages. By obtaining information on actively held patents, we cover all dimensions of patenting, externally acquired as well as internally generated patents. Further, 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% of firms hold their patent over the maximum length (IP5 2018). Moreover, 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.

To achieve this, we exploit unique data which comprises in-depth legal European patent data

[2]According to Peters and Taylor (2017), 80% of intangibles are generated internally and not through acquisition.
[3]In comparison, in the U.S. patent system, renewal fees are due only three times over the course of 20 years which makes an equivalent measurement strategy impossible.

(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 enrich this data with detailed, hand-collected information on patent fee schedules for all European countries, enabling us to calculate exact values for firms' annual patenting expenses.

We extend 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 measurement approach appears promising, because the patent stock is likely to represent a more accurate measure of firms' intellectual property than other (patent-related) approximations. We thereby provide comprehensive insights on the effect of patenting on debt financing for a variety of firms and industries. For example, 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. Importantly, by introducing novel patenting measures, we shed new light on companies' financing activities. Finally, by investigating a major legislative change, 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, 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.[4] Compared to the rich literature testing for the presence of financing constraints, we focus on inventive outcomes as a mean to eliminate constraints for innovation-oriented firms.

Thus, our paper directly adds to the literature on the use of intellectual property for obtaining outside funding, in particular debt financing.[5] While the use of easy to liquidate *tangible* assets is conventionally considered the prime mode for collateralization, an evolving strand of literature explores the use of *intangibles*. For example, Loumioti (2012) estimates that the use of intangible assets securing syndicated loans increased from 11% in 1997 to 24% 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 2019), 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.* (2020) argue that obtaining a patent causally facilitates access to various external funding sources for young firms.

Closest to our paper is the work by Mann (2018), who studies how patents are explicitly included in loan contracts. The author shows that patenting companies raise more debt and spent

[4] There are several inherent reasons why inventive firms face difficulties in obtaining debt finance (see e.g. Stiglitz and Weiss 1981, Stiglitz 1985, Berger and Udell 2006). First, debt contract structures are not well suited for research-intensive firms with uncertain and volatile returns. Second, adverse selection problems are more likely in technology-intense industries. 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. Finally, the limited collateral value of intangible assets restricts the use of debt.

[5] For a detailed overview on the role of collateral in funding decisions, see Graham and Leary (2011).

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 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. Importantly, our unique institutional setting allows us to generate patent value measures applicable for all European firms. This way, we shed new light on the relevance of patenting for attracting debt across the entire business landscape.

The remainder of the paper is organized as follows. Section 2 introduces our patent measurement strategy, including plausibility tests and descriptive evidence. In Section 3, we describe the data and our empirical approach. In Section 4, we present our empirical results, including the assessment of potentially confounding factors, robustness tests and an analysis on heterogeneous treatment effects. Section 5 concludes.

2 Measuring firms' innovation stock

2.1 Patent renewals: the institutional framework

Intellectual property rights (IPR) are designed to allow appropriation of returns from their owners' investment in intangible assets. Just like tangible property, they may carry inherent value and frequently constitute a substantial part of overall firm value. As one specific form of IPR, patents are exclusive rights on products or processes that provide new technical solutions to a problem.[6]

In general, patent systems and, in specific, their maintenance systems notably differ from country to country. In this context, a combination of cost-related institutional elements of the European patent system as stipulated by the European Patent Convention (EPC)[7] are key for our analysis. In Europe, patenting fees are relatively high which raises the economic relevance of respective costs. Figure IA2 (Internet Appendix B) compares international fees and payment structures also with other main jurisdictions. For example, maintaining a patent in Europe is between five to twenty times more expensive as compared to the US (de la Potterie 2010). Patent applicants have to pay filing and administrative fees to activate the protection on their invention. Usually beginning with the third year after initial patent filing, the patent holder then has to pay renewal fees to perpetuate protection. These maintenance costs comprise two separate components. Renewal fees have to be paid in every year *and* in accordance to the geographical scope of the patent,

[6] By law, each patent is fully disclosed after publication making them a valuable source of information for a variety of different parties. The Internet Appendix C summarizes considerations on how patenting supports external debt financing in detail, both from a theoretical economic (*de facto*) perspective and a legal (*de jure*) perspective.

[7] As of March 2020, 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.

i.e. in how many EPC countries patents are active. Thus, patent protection can be maintained independently across national patent offices such that patent holders choose every year where to maintain protection on a country-by-country basis. Figure 1 graphically illustrates how these two aspects affect total patenting costs. There are two main insights. First, because each additional jurisdiction in which a patent is active increases the amount of renewal fees, patenting costs vary substantially depending on the number of designated countries (see Panel A). Second, for a patent held in multiple jurisdictions over its maximum protection period, renewal costs constitute the vast majority of expenses (Panel B). Moreover, the European renewal scheme is important not only because of the economically relevant height of patenting costs but also because they precisely allow identifying patent owners. According to the EPO (2018), 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 at every point in time. Against the background of our research agenda, the combination of the frequency and magnitude of renewal fees makes the analysis of European patents particularly interesting.

- Insert Figure 1 here -

To exemplify the implications of different fee schedules, we compare the validation rates of patents filed at EPO and United States Patent and Trademark Office (USPTO). This is because the USPTO collects payments only after 3.5, 7.5, and 11.5 years, respectively. For example, a respective patent is therefore valid in all US states until the maximum length of 20 years once renewed 11 years after filing. Figure 2 shows that patents are typically not maintained for the maximum length of 20 years but are lapsed before in the majority of cases. This resembles a depreciation in patent values: As technological progress evolves over time, an invention today may not be meaningful in the future anymore, depreciating the value of a patent. Notably, the fraction of patents held for an extended time is much larger at the USPTO compared to grants from EPO. While 50% of EPO patents are held seven years after application, 50% of USPTO patents are maintained for about 17 years possibly because US renewal fees do not have to be paid annually and are significantly lower. Plausibly, a patent is more likely to be perpetuated despite not being actively if it is valid in the US as compared to Europe, as opportunity costs over time are relatively low. The European fee schedule therefore seems suitable for explaining the underlying values of respective patents.

- Insert Figure 2 here -

2.2 Measurement strategy

Against the background of the described institutional features and the relevant patenting dimensions, we now illustrate our measurement strategy. By observing the annual renewal payments, we can exactly identify the size of a firm's patent portfolio. Specifically, we first determine each year at which a patent is held by a firm to then sum up the total number of actively held patents in each year. This gives us the size of the patent stock. Yet, this measure by itself explains patent value only to a limited extent. We therefore include information on the number of jurisdictions each patent within a portfolio is held (i.e. the so-called family size), for every year we observe in our sample. Literature identifies both the geographical scope and the number of patent renewals to closely related to patent value. For example, only particularly valuable patents have a large international scope (Harhoff *et al.* 2003) and are maintained over a long period (Schankerman and Pakes 1986). Hence, firms' willingness to incur these costs plausibly reflects the lower bound of expected patent value.

We complement these dimensions with an additional, unique feature. Specifically, we take into account that the EPC payment scheme is not symmetrical across patent life and designated jurisdictions. 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. While this rising fee structure applies across all EPC jurisdictions, the exact amount is different in every country and for virtually every year. We therefore hand-collect the precise Euro value in a patent-year country matrix (see Table IA1 in the Internet Appendix A). Combining these prices with the information on active jurisdictions and patent age allows us to calculate firm-level renewal expenditures on an annual basis. For calculating total patenting expenses, we further include common fees that arise during the first years after submission of the patent application. While there are no renewal fees within the first two years in most (but not all) jurisdictions, firms incur costs related to patent application and grant.[8] For each firm-year observation, we add up all costs items for each firm-year observation. This is a particularly valuable feature because it enables us to assign concrete values to internally generated patents on virtually all patenting firms irrespective of size or legal structure.[9] In our empirical analysis we refer to this measure as total patenting costs. For illustration, Table IA2 (Internet Appendix A) calculates the patent costs for the average sample firm. To ensure that results are not sensitive to the distinct variable definition and to address concerns regarding industry and cyclical heterogeneity of patenting activities, we normalize all patenting variables on an industry-year basis[10] and include different variants of the measures in robustness test. This approach should mitigate concerns regarding strategic patenting behavior which is correlated with industry- and time-specific characteristics of firms (Lerner and Seru 2017). Summarized, we define the two main patent measure as:

[8]Fees due at the time of application include patent examination fees, international search, translation and filing fees. Additionally, firms have to pay designation and grant fees which are due at the time of patent approval. Finally, we expect national renewal fees to become applicable, with the fourth year after application. This is consistent with previous literature (e.g. Harhoff and Wagner 2009) showing that patents are granted on average four years after application and then enter the national phase. Because it is not unambiguous to appoint these payments to specific dates, we sum all application- and grant-related costs and assign them evenly to the first three years of patent life.

[9]For example, Kogan *et al.* (2017) use stock market reactions after patent publication to assign dollar values to patents. This approach is best suited for publicly traded firms and not for small private firms. Giuri *et al.* (2007) assign prices for patents by self-reported estimates of their inventors. Despite concerns about self-reporting, this approach is hardly scalable to a large sample such as ours. Overall, we consider our approach as a conservative way to measure expected patent value because the option to prolong a patent at any given point in time may also depend on the future possibility to maintain the patent for all subsequent periods. Note, that the value of this option is larger for relatively young patents, i.e. when the remaining period of the temporary monopoly is relatively large.

[10]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. Our main findings are robust to using non-normalized variables.

$$\text{patent stock}_{it} = act.\ patents_{it} \times jurisdictions_{it} \quad \text{and} \tag{1}$$

$$\text{patent costs}_{it} = \sum_{1}^{P} fees_{pt} \quad , \tag{2}$$

where $act.\ patents_{it}$ is the number of active patents of firm i at time t, $jurisdictions_{it}$ equals the year-specific average number of jurisdictions of all patents in a given portfolio (i.e. $act.\ patents_{it}$), respectively. Patenting costs are a function of these two parameters and patent age. These costs equal the overall costs to hold patent portfolio P which is the sum of all individual patents fees paid to file and maintain patents $1 \ldots p$ in year t.

2.3 Patenting costs and the quality of innovation

One important threat to our measurement strategy would be if the relatively small size of renewal fees screens out only the left tail of the patent quality distribution. Literature shows that market values of patents do not only strongly vary (e.g. Gambardella *et al.* 2007) across patents but they can also reach significant economic amounts. For a sample of European patents, Giuri *et al.* (2007) document that about one-third of patents have a (self-reported) minimum market value of more than one million Euro. This exceeds the patenting costs that we can directly measure, particularly because in our case patenting costs have a maximum value by definition. For one individual patent, renewal costs cannot exceed approximately 200,000 Euro because the number of renewals and jurisdictions are bounded by institutional features. Thus, while our measure should certainly be informative about variation in the lower part of the value distribution, a potential caveat could be that it fails to explain high impact patents.

To test whether annual patenting costs are a predictor for high quality patents, we relate our measure to existing patent indicators associated with market value. Specifically, we analyze the relationship between our measure and a) citations received by patents in firms' portfolio, measuring technological and market value which is unrelated to patent costs and b) the generality of respective patents which proxies for patents' probability to contribute to economic growth.[11]

- Insert Table 1 here -

Table 1 displays summary statistics on patent stock and -costs measures as well as common indicators of patent quality. The table does not include observations with zero patents (i.e. about 30 percent of observations). In line with common associations of inventive activities, all variables are highly skewed towards low-quality and small sized portfolios. Benchmarking these statistics to

[11] First, the number of citations received mirror the technological quality of the underlying invention. In this context, de Rassenfosse and Jaffe (2018) find that contributions to quality also enhance value (while the reverse is not necessarily true). We thus follow previous literature by considering the number of citations received as measure for technological importance and economic value. Second, patent generality captures the distribution of received citations with regard to different technology classes these citations originate from. We use the patent generality index as proposed by Hall *et al.* (2001) which previous literature uses, for example, to identify particularly valuable technologies covering general purpose inventions (Hall and Trajtenberg 2004). Higher values indicate that the patent is relevant for a larger number of inventions across a wider range of technology classes.

related studies shows the consistency our sample. For example, in our sample about 19 percent of patents receive no citation compared to 16 percent in Kogan *et al.* (2017). Similarly, patent stock and cost measures are right skewed. Importantly, these measures have higher variation than the common quality measures for low-quality patents, while presenting a similar shape in the distribution with regard to high values.

At a first glance, our approach delivers expected low patent costs. The median cost per patent is 1,400 Euro and the median portfolio cost is 26,600 Euro (i.e. multiplying the median number of patents with the median costs). With an average patent life in our sample of eleven years, this resembles a net value of about 300,000 Euro. Putting these numbers into perspective is important. As such, these rather low values are consistent with the fact that the median patent is not very influential for subsequent innovation as indicated by both patent citations and the low generality index score. Moreover, relatively important patent portfolios are also significantly more expensive. For example, a patent portfolio in the top five (one) percentile incurs costs of approximately 8.3 million Euro (49.4 million Euro).

Figure 3 relates the average number of citations received to the average patent costs of a firm. Average patent costs are higher for firms which hold a patent at more jurisdictions and over a longer period of time. To ensure comparability, we only consider citations received during the first eight years after filing. The scatter plot illustrates that higher costs reflect higher average citations received. Conversely, if we use patent filings or just the size of the patent stock, the average citations are virtually unchanged for high or low values (see Figure IA3 Panel A and B, respectively in the Internet Appendix B). It is important to note that all measures are independent from firm size suggesting it is unlikely that increased patent activity in absolute terms accounts for these results. Results are robust to using the logarithm of patent costs and the patent cost to asset ratio (Figure IA4 Panel A and B, respectively in the Internet Appendix B). These findings suggest that higher technological quality of the underlying inventions is positively related to our measure of patent value.

- Insert Figure 3 here -

To further explore this relationship, we test whether our measure is not only positively related to patent quality but is also able to explain truly important technological inventions. We therefore deploy the patent generality measure as proxy for particularly influential patents. Instead of analyzing the average values of patent generality, we consider the top values of generality within patent portfolios. Specifically, we estimate top 25, 10, and 1 percentile of the portfolios, respectively. The general idea is that despite average higher technological quality, truly novel patents are only captured by regarding the right tail of the generality distribution. Choosing these relatively broad categories accounts for the fact that many firms have only relatively small patent portfolios. We relate the total patenting costs of a firm i normalized by its industry-year cohort to these estimated values of novelty:

$$\text{generality}_{it}^{q} = \gamma + \gamma_1 \text{patent costs}_{it} + \gamma_2 X_{ij} + u_{ij} \quad \forall \;\; q \in \{25, 10, 1\}. \tag{3}$$

The vector X controls for i) observable time-invariant firm characteristics by including firm fixed effects, ii) observable time-variant firm characteristics that relate to firms capital structure decisions by including a set of control variables (i.e. firm size, profitability, share of tangible assets, and cash flows), iii) firm-year fixed effects that account for macroeconomic changes along the sampled time frame and, in particular, iv) institutional cost differences, country-industry fixed effects which account for industry specific patenting behavior. Standard errors are heteroscedasticity-consistent and clustered at the firm level. Table 2 presents the results. We find a strong positive relation between our patenting cost measure and the presence of patents with a probability to contribute to economic growth.

- Insert Table 2 here -

Combining these insights suggests that our patenting measure is able to capture variation along the quality spectrum of firms' inventions. While the face value of the measure can be interpreted as the lower bound of expected value, our measure explains variation in the upper tail of the patent value distribution. Importantly, particularly high patenting costs also identify truly novel inventions. This leads us to assume that costs do not resemble the exact market value of patents but they rather mirror firms' willingness to pay and thus proxy value proportionally. Despite being a rather conservative approach in measuring value, patent costs provide useful information across the entire distribution of patents.

3 Patenting and leverage: the empirical approach

3.1 Data 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.[12]

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,

[12] 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.* 2009). 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.

Denmark, Finland, France, Germany, Ireland, Italy, the Netherlands, Sweden, and the United Kingdom). Table IA3 (Internet Appendix A) displays the sample distribution across countries.[13]

- Insert Table 3 here -

Table 3 provides summary statistics on financial and patenting variables of sample firms. To avoid biased estimates from outliers, we truncate variables at the 1st and 99th percentile. Sample firms are on average 27 years old (with a median age of 18 years) and are privately-held (only 5.3% of the original sample are publicly listed). Most importantly, descriptive statistics show that patenting activities vary strongly across firms. While the average firm holds about five patents, the maximum portfolio size is 2,684 patents. Similarly, patents are renewed on average seven times and valid in nine jurisdictions, whereas some patents are never renewed or only valid in one jurisdiction. Patenting intensities also vary across industries. Table IA4 (Internet Appendix A) displays the distribution of firms across two-digit NACE Rev.2 main categories. The majority of firms (56%) belong to the manufacturing sector.

3.2 The Enforcement Directive as identifying event

To study the causal relationship between patenting and firms' debt capacity, we use a natural experiment that affects firms' legal environment by improving patent protection and enforcement. Explicitly, we exploit the EU Directive 2004/48/EC (Enforcement Directive) as an identifying event affecting the value of patent portfolios. The general objective of the Enforcement Directive is to harmonize 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.

Our identifying assumption is that the change in law enhances the fundamental value of patents. Because inventions are often not alienable in contracts and are thus subject to ownership conflicts and piracy, a more thorough enforcement helps firms to prevent unlawful use of their technology. Patent value thus 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. For example, 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

[13] From the original EU-15 member states at the onset of the sample period in 2000, we drop five countries due to inconsistent data availability (Austria, Greece, Luxembourg, Portugal, and Spain). Except of Italy, the distribution of observations among countries represents the actual population shares.

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. In Europe, this circumstance is emphasized by the fact that patents have to be activated in each EPC Contracting State on an individual basis.[14]

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. Hence, we expect strengthened property rights enforcement to enhance patent value. Consistent with this, ceteris paribus, exogenous variation in patent protection should causally lead to changes in firms' leverage.

In order for the Enforcement Directive to be a viable event, the change in law should have quantifiable effects. 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). A comprehensive evaluation study of the EU (2017) ascertains that the Enforcement Directive is an effective tool to harmonize enforcement of IPR on a general level. In a multi-country setup like our analysis, these aspects are particularly crucial. The study further shows that the new rules help effectively to protect intellectual property and prevent IPR infringements. More specifically Fleissner (2009) finds the amendments to enhance resilience against illegal copying and thereby strengthened the role of IPR.[15]

For several reasons, the Enforcement Directive's effects on firms' patent portfolio is plausibly exogenous. 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 IA6 in the Internet 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.

[14] Further, from an investor's perspective, patents become a more valuable asset, because improved enforcement decreases the level of uncertainty regarding potential appropriation of returns. This also has potential beneficial effects on patents as a credible quality signal making.

[15] Internet Appendix D provides further details on the effects of the Enforcement Directive. Table IA5 (Internet Appendix A) summarizes the articles of the Directive.

To further mitigate endogeneity concerns, 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 locations where their patent portfolio is active. Given the complexity of legal procedures and the associated time lags, we presume it 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 effect of the Enforcement Directive.

3.3 Econometric model

The institutional setting allows to estimate 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. 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. 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. As time-varying control variables, we use the well-established firm characteristics that determine their debt-equity choices: i) size, ii) profitability, iii) tangible collateral, and iv) cash flow. Table 4 defines these capital structure determinants. We cluster standard errors by firms in the main specification (Equation 4):

$$\text{Debt-ratio}_{it} = \alpha_1(\text{Affected}_i \times \text{Post}_{ct}) + \alpha_2 \text{Patent value}_{it-1} + \alpha_3 CS_{it} + \varphi_i + \delta_{ct} + \varepsilon_{it} \ , \qquad (4)$$

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 the end of period t. $\text{Patent value}_{it-1}$ describes the patenting value of firm i's patent portfolio as defined in Equation (1) or, alternatively, in Equation (2).

- Insert Table 4 here -

For the treatment variable, $Post_{ct}$, we use two complementary definitions as discussed in the previous subsection. First, 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. Arguably, the cross-country variation in the treatment variable according to this definition is rather low. In addition, this variables does not reflect that patents are held across various jurisdictions in addition to the home market. In a second definition, 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. Panel A in Figure IA5 (Internet Appendix B) displays the average treatment value of this variable for all sample firms. To illustrate the variation across firms, Panel B displays the treatment variable values for 12 randomly selected sample firms.

In our setup all firms are treated because the Directive does not only apply to certain subgroups but rather affects all firms within the respective jurisdiction. For 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. We assume that firms with a large number of valuable patents ex ante should benefit disproportionally from the change in law improving the enforcement of respective patents ex post. 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. Affected$_i$, is a binary variable indicating whether we expect a firm to be strongly affected by the treatment according to this definition or not. 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.

3.4 Verifying the empirical strategy: DID assumptions

Table 5 provides key characteristics of affected and control firms, i.e. high and low ex ante patentees. The two groups do not differ with respect to profitability or cash flows. However, they are significantly different regarding size dimensions. Control firms are smaller, younger, and less frequently public firms. In line with this, they are supposedly more dependent on external debt, which is reflected in higher debt-ratios as compared to affected firms. Qua definition, affected firms differ from unaffected in dimensions related to patenting. This is not only reflected in direct patenting measures but also in a statistically significantly lower share of tangible assets. Accounting for confounding factors arising from these differences is essential for our empirical analysis.

- Insert Table 5 here -

Given these observable difference, we compare changes of respective covariates across pre- and post treatment periods. Essentially, these differences do not invalidate our empirical strategy as long as they are stable over time. Table IA7 (Internet Appendix A) therefore displays mean values of the common capital structure determinants and suggests that these covariates remain relatively constant and/or vary uniformly for both affected and control group firms. Hence, confirming our empirical design, changes in treatment exposure are not associated with changes in these covariates.

Importantly, despite differences in levels, a key assumption in our DID setting is that firms have to follow a common path in the absence of the treatment, while differing in its presence. We therefore analyze whether leverage trends during the pre-treatment period are the same for both firms with ex ante high patent stock values and those with low values. As a precaution, we test for parallel pre-trends in three different ways.

First, 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 (4). If firms move along similar paths, estimates on these interactions should not be statistically significant from zero during the pre-treatment period. Figure 4 graphically displays the correlation coefficients and the corresponding 95 percent confidence intervals of the interactions using the regression setup from Equation (4) which controls for other capital structure determinants and country-year fixed-effects. In none of the years preceding the implementation of the Enforcement Directive, correlation coefficients are statistically different from zero. We repeat this analysis using the pre-treatment median split of patenting costs as definition for whether a firm is affected by the treatment. Determining affected and control group firms by their ex ante patenting costs leads to equivalent results (see Figure IA6 Internet Appendix B).

- Insert Figure 4 here -

Second, we show in Table IA11 (Internet Appendix A) that these results are not sensitive to applying different treatment specifications by repeating the underlying regression of Figure 4. None of the estimates indicates a significantly different trend between affected and control group firms' leverage ratios before the treatment. Third, we follow Angrist and Pischke (2008) by including both a trend variable (i.e. a running number of the sample years) and an interaction of the treatment dummy variable with this time trend in a regression estimation resembling our baseline specification for the pre-treatment years. 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. Estimates displayed in Table IA12 (Internet Appendix A) confirm exactly this.

The parallel trend assumption can never be fully approved in empirical analyses, but their absence can be rejected. Applying these different methodologies and using multiple specifications for each does not allow us to reject that affected and control firms move along a common path prior to the treatment. Our results thus provide strong evidence supporting the parallel trend assumption and the validity of our econometric strategy.

To complete this picture, we repeat the same analysis but use mean values of firms' debt-ratios both before and after the treatment occurs (see Table 5). In line with our estimation strategy, we do not observe a statistically significant difference in means for firms that are not considered to be affected by the treatment. Most important, however, firms with an ex ante high value patent stock increase their leverage by about 2.0 percentage points (15.4%). 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 our second definition that relies on the ex ante patenting costs of the patent portfolio defined by Equation (2). This adjustment does not affect the results.

- Insert Table 5 here -

4 Empirical results

4.1 Firm-level patenting values and debt financing

Figure 5 correlates the size of firms' patent portfolio with 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.[16] 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 5 here -

Table 7 displays results on different variants of the main specification (Equation 4). Across specifications, estimations suggest a disproportionally positive effect of the Enforcement Directive on treated firms' debt ratios. Results are not only statistically but also economically significant. For example, coefficients from the DID estimators of our main specifications that use the patent expenditure definition of patent value (Columns VII and VIII) suggest that the average affected firm increases its leverage by 10.5 (Column VII) and 16.8 percent (Column VIII). 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 IA8 and IA9 (Internet Appendix A), respectively.

Approximating patent value by firms' annual expenses allows us to assign Euro values to the effects. These can be inferred from the estimation specifications that use the interaction of the continuous patenting measure with the post dummy (Columns II and VI). For both patent value definitions effects are positive and statistically significant at the one percent level. In economic terms, the coefficient (3.513 in Column VI) implies that one standard deviation increase in patent expenditures translates to a a 8.2% (1.2 percentage points) increase in debt ratios for firms with ex ante high patenting costs. The same coefficient suggests that moving the median firm to the 75$^{\text{th}}$ percentile of the patent cost distribution (resembling an increase of about 18,000 Euro in annual patent expenses) leads to a 20.2% increase in the respective firms' debt ratio (resembling and increase of external debt amounting to 130,000 Euro).[17] The difference between patent expenses and additional funding reflects the notion that these expenses resemble the lower bound of the actual patent value.

- Insert Table 7 here -

To assess the importance of how to proxy patenting activities, Figure 6 plots the DID estimators from our main specification. We repeat the main specification (Equation 4) but vary the treatment

[16] Similarly, recasting the binned scatterplot with patent fillings instead of the actual patent stock suggests that filings do not explain heterogeneity in leverage ratios either (see Figure IA7 in the Internet Appendix B).

[17] We calculate these Euro value increases by assuming that the percentage increase in the median debt-ratio of affected firms can be set equal to the percentage increase in the median debt value. In our sample, the median value of treated firms' debt amounts to 650,000 Euro. As a further explanation, strictly interpreting this example implies a multiplying effect of patenting expenses for the median firm of more than seven. Conversely, moving the median firm to the 25$^{\text{th}}$ quartile reduces annual patenting costs by 6,000 Euro and lowers debt by 55,000 Euro. This implies a multiplier of about nine and suggests a non-linear relationship between patent value and firms' amount of debt.

indicators. We use the two main measures as defined by Equations (1) and (2) in the first two rows as well as three broader measures of firms patenting activities. Here, we first split the patent stock variable into its single components, i.e. the stock size (third row) and value (fourth row). Using these variables results in positive and statistically significant coefficients in both cases. However, the size and the precision of the estimates are weaker compared to their combined use. This suggests that size and value are important complements for the effect of patenting on firms' ability to attract debt. In the fifth row a firm is considered to be treated if it files at least one patent during the year preceding the first implementation of the Enforcement Directive in any relevant jurisdiction for the respective firm. Here, the coefficient of the DID estimator is statistically not different from zero.

- Insert Figure 6 here -

As a next step in our main analysis, we analyze the timing of the treatment effect in detail. We proceed in two different ways. First, as a plausibility test we test whether the treatment leads to quantifiable effects on the announcement date. Second, we study the effect of the treatment with time since exposure.

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. Effects should be primarily observable once the Directive becomes effective and not when it is announced. We therefore assess whether the effect of the Enforcement Directive is already measurable at the time of announcement in 2004. 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 29$^{\text{th}}$, 2004 by the European Parliament and the Council, and zero otherwise. We test the effect of the announcement of the Enforcement Directive both on the patent value variables from Equations (1) and (2), and on the respective treatment group definitions.

Table 8 displays estimations first on the full sample (Columns I-IV). Estimates are positive and significant to varying degrees. Compared to the baseline scenario the values are, however, substantially smaller. Again, these positive results are not surprising, given that the artificial treatment period includes also the true treatment period. To gain a better understanding on the announcement effect, we also implement specifications that exclude all years in which both the placebo and the true indicator equal one (Columns V-VIII). Now, all estimates become even smaller. None of the results is statistically different from zero. This speaks against the hypothesis that already the announcement of the Enforcement Directive has a quantifiable impact on the firms' debt-equity choice. Hence, this set of tests does not support the hypothesis that the announcement effect can serve as an alternative explanation for our main results.

- Insert Table 8 here -

Finally, we deploy an event-study design for analyzing the lag structure of the treatment effects. Figure 7 first presents graphical results by plotting lead- and lagged treatment variables, i.e. the interaction of year dummies with the indicator on whether a firm is categorized as affected by the treatment or not. Confirming our previous results, estimates on correlation coefficients in the pre-treatment period are low and 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, increase over time and are statistically significant (at the one percent level from t+2 onward). In contrast, for the group of control firms there is 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 diffuses gradually, especially in the case of harmonization processes, which are dependent on mutual implementation of the respective change in the legal framework. We obtain an equivalent picture when using ex ante patenting costs to determine affected and control group firms (see Figure IA8 in the Internet Appendix B).

- Insert Figure 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 IA13 (Internet Appendix A) illustrate the time structure of the treatment impact and differentiate again among four different treatment specifications. Column I and II display results on high ex ante patent stock firms and ex ante patenting costs, as defined in Equations (1) and (2), respectively. For these specifications, effects become increasingly measurable after treatment. Using the single components of the patent stock variable as defined in Equation (1), shows that effects on the size and value of firms' patent portfolios do not provide a similarly consistent pattern as compared to their simultaneous application. Again, this result strengthens the view that the two components are important complements. Finally, for patent filings no effect of the treatment is measurable throughout the entire post-treatment period (Column V). All of these findings are in line with our previous results on the main specification.[18]

4.2 Patenting versus non-patenting firms: CEM matching approach

Our main sample comprises firms which hold at least one active patent during at least one year between 2000 and 2012. Hence, our main analysis compares patenting firms with regard to their ex ante patenting intensities. Our identification strategy assumes that firms with a relatively high ex ante patenting intensity are disproportionally affected by the treatment. Descriptive statistics

[18] Our analyses so far do not solve one remaining methodological issue: The varying treatment over time produces overall estimates that are weighted by the conditional variance in treatment (Goodman-Bacon 2018). This implies that early-adopting member states eventually have higher weights in our results than others. As an additional robustness check, we thus repeat our baseline regressions but exclude early-adopting firms, i.e. those treated before 2007. The estimated coefficients are virtually equivalent to those reported in the main analysis.

reveal (i.e. Table 5) that these two types of firms exhibit different characteristics not across all but across important dimensions, such as firm size, age, or their tangibility of assets. While these differences are symmetric comparing pre- and post-treatment differences (see Table IA7), they remain a threat to our identification strategy and potentially confound our results. We therefore propose an alternative approach to our estimation method. Specifically, we match sample firms with non-patenting, out-of-sample firms based on observable firm characteristics. We obtain potential matching candidates to our sample of patenting firms from our original Amadeus dataset. This allows us to compare pairs of very similar firms which differ only by their patenting activities.

For obtaining these control group firms, we use Coarsened Exact Matching (CEM) as proposed in Blackwell *et al.* (2009). CEM allows assigning each firm into stratas, which share pre-defined matching characteristics during the pre-treatment period, and assigns one or more patenting firms to one or more non-patenting firms. In order to account for firm-specific and macroeconomic heterogeneity, we match based on the pre-treatment mean values of firm size, profitability, tangibility, cash flow, debt-ratios (all variables are defined as in Table 4), and age categories. Further, we impose matching pairs to share the same country and industry (NACE Rev. 2 main category).[19] Overall, this approach results in a sample of 17,708 firm-year observations out of which 8,389 (9,316) observations are from patenting (non-patenting) firms. Table 9 presents summary statistics distinguishing among patenting and matched firms. Across all relevant dimensions these firms have comparable properties, i.e. non of the differences in means is statistically significant.

- Insert Table 9 here -

Arguably, the only difference among the two groups is their patenting activities. Because our identifying event should only be relevant for firms that actually patent, the treatment should not have an effect on the matched non-patenting firms. We test this estimating the following equation using our matched sample:

$$\text{Debt-ratio}_{it} = \gamma_1 \text{Patentee}_i + \gamma_2 \text{Post}_{ct} + \gamma_3 (\text{Patentee}_i \times \text{Post}_{ct}) + \gamma_4 CS_{it} + u_{it} \ , \tag{5}$$

which uses variable specifications as defined in Equation (4). The estimation explains the effect of the Enforcement Directive (indicated by the country-specific dummy variable $Post_{ct}$ for country c) the debt ratio of firm i at time t, differentiating among firms with ex ante patenting activities and the matched control group which does not patent. The indicator variable ($Patentee_i$) equals one (zero) if firm i belongs to the treatment (control) group.

- Insert Table 10 here -

Table 10 contains the results of this approach as well as further model specifications. The results are clear in showing that being a patenting firm does not help explaining firms' debt ratios

[19] The age categories are: 1: $\leq$2, 2: $3-5$, 3: $6-10$, 4: $11-15$, 5: $16-25$, 6: $26-50$, 7: $51-100$, and 8: >100 years, respectively. For the five matching variables (i.e. size, profitability, tangibility, cashflow, and debt ratio) we use 30 equally sized bins.Whenever certain observations fall into a bin without closest neighbor, this observation is not considered for a match.

(Columns I-III). Similarly, the implementation of the Enforcement Directive, does not relate to debt (Columns II-III). These findings are consistent with the empirical strategy of our matching approach. In contrast the coefficient of the interaction term (α_3 in Equation 4) is positive and statistically significant suggesting that patenting firms increase their debt ratios with the onset of the treatment. This effect is robust to applying a rich set of fixed effects. Firms in control and treatment groups are comparable in terms of the pre-treatment characteristics and only differ in terms of patenting activities. Hence, these results provide strong evidence that only those firm for which a patenting-related legal change is relevant respond to the treatment. The effect is also economically significant: the coefficient on the interaction term in Column III implies that the average ex ante patenting firm increases its debt-ratio by about 17 percent (or 1.7 percentage points) relative to the control group.

4.3 Alternative mechanisms: testing potential threats to identification

A central assumption in our main analysis is that both affected and control group firms would exhibit similar trends in the absence of the treatment. A causal interpretation of our baseline results therefore requires that our treatment is not correlated with omitted variables that affect firms' debt financing. One likely alternative factor within our sample time frame is the financial crisis. In several steps, we thus test whether our results can be similarly explained by using the crisis as an exogenous shock affecting firm-level capital structures. While the financial crisis occurred after the Enforcement Directive passed into domestic legislations across sample countries, we further test for omitted factors preceding the amendments. A related omitted factor that potentially leads to differential trends even in absence of the treatment could be firm size. The number of patents held by a firm is related to its size (see e.g. Table 3). One plausible concern is that larger firms might increase their debt ratios at different rates, particularly during the times of the recession. The second part of this section therefore tests our findings regarding firm size.

4.3.1 The financial crisis and borrowing

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 jurisdictions during the years preceding the crisis, a potential explanation for our results could be that patenting firms were systematically differently 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 economic 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 them is non-trivial. However, if the adverse events in financial markets during the late 2000s are indeed the main driver of our results, using the financial crisis as the treatment should lead to more pronounced - or at least similar - effects relative to our treatment measure.

- Insert Table 11 here -

We test whether this is the case in multiple ways. In the most simple approach, we exchange the treatment variable with a country-specific dummy ($crisis_{ct}$) that is equal to one if the home country c of a firm experiences a recession in period t. 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 was negative and unemployment rates increased for at least two consecutive quarters and vice versa. Table 11 displays regression results from the baseline specifications using the crisis as a treatment dummy (Columns I-IV). Compared to the baseline scenario, the coefficients are also positive and in several instances statistically significant. Because the timing of the treatment and the financial crisis overlap, it is generally plausible to obtain these results. The magnitude and level of significance is yet substantially smaller. To test for robustness of this specification, we use an alternative specification in which we truncate the sample by the country-specific end of the financial crisis (Columns V-VIII). We define the crisis by a binary indicator variable that is equal to one for the years after 2008. In this case, when using the crisis as artificial treatment variable, results are even weaker as compared to the first test.

Because we obtain positive and partially significant results in some instances of the previous tests, we run a third test that assesses the importance of the crisis effect relative to the treatment effect. If the financial crisis was better able to explain the baseline effects, we would expect that including both Enforcement Directive and crisis variables simultaneously as treatment indicators delivers larger estimates for the crisis variables. Table IA10 (Internet Appendix A) displays this test applying various model specifications. Results are unambiguous: Across all specifications coefficients on DID estimators using the crisis as treatment variable are small and statistically not different from zero. In contrast, all coefficients using our treatment variables on the implementation of the Directive remain large, positive, and of highest statistical significance. Based on the insights from these threefold tests, it appears unlikely of the financial crisis to qualify as an alternative mechanism explaining our baseline results.

In the previous tests we cannot confirm that the crisis similarly affected borrowing behavior of our treatment group as compared to the implementation of the Enforcement Directive. However, these tests only partially rule out the alternative explanation that our estimates from the baseline specification are indeed resulting from the crisis. Essentially, effects might as well be driven from the ensuing 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.

In our sample, we observe about 80% of firms during the entire time frame between 2007 and 2012. Hence, we know that these firms survived the crisis with certainty. If surviving firms drive the results, we would expect more pronounced effects if we re-run estimations 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 for firms that are observed at least five (out of six) times between 2007 and 2012.

- Insert Figure 8 here -

Figure 8 displays the results of this exercise graphically. Coefficients on the DID estimators are virtually equivalent across multiple specifications of our baseline setup. Only when using the binary indicator for high ex ante patenting costs to determine affected and control firms, we obtain a positive but insignificant effect on the respective coefficient. Overall, we still cannot confirm that results are particularly pronounced for firms that survived the financial crisis. Concluding, 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 to be driven by alternative factors arising from the financial crisis.

4.3.2 Firm size, asset tangibility and the effects of patent portfolios

Because the staggered implementation of the Enforcement Directive across sample countries is arguably centered around a few years, the main cross-section identifying variation is the sorting of companies into their ex ante patenting intensities. Of course, firms' number of patents is strongly related to their size. While our measure is not replicating a mere patent count, it is still important to test whether affected and control group firms exhibit differential trends during the treatment period because of size differences.

Differences in size are crucial, because they directly correlate with firms' propensity to be financially constrained (e.g. Almeida *et al.* 2004). Constrained firms are particularly prone to adverse economic shocks. The timely proximity of the treatment to the financial crisis suggest that firm size is, potentially, an omitted factor explaining our main results. To rule out this threat to our identification strategy, we test whether firm size is a better explanatory factor for our findings as compared to firms' ex ante patenting intensity.

We address this issue empirically, augmenting our baseline regression by additionally including an interaction term of firm size with the treatment variable. Table 12 summarizes results on regressions that use different variable specifications both for our treatment measure and the size variable (i.e. using both an indicator variable for large firms and a continuous measure). Coefficients on the interaction terms of size and treatment are positive but only in one specification significant. In contrast, coefficients on the DID estimators from our main specification remains positive, much larger in magnitude, and are highly statistically significant. These results are consistent across specifications suggesting that firm size is not an omitted factor that can be accounted for driving our main results.

- Insert Table 12 here -

While these tests are important in demonstrating that our results are not simply driven by firm size differences, they remain silent regarding whether different firm sizes are differently affected by the treatment. To gain a better understanding on this issue, Figure 9 displays DID-estimators explaining the effect of the Enforcement Directive on firms' debt ratio according to different firm sizes obtained from repeated baseline regression (Equation 4). The sample is split according to firms' average number of employees during the pre-treatment period between 2000 and 2004. Firms with, on average, less than 100 employees are categorized as small, firms with 100-500 employees are categorized as medium-sized, and firms with at least 500 employees are categorized as large, respectively. As a precaution, we use both treatment definitions, i.e. in the left (right) part of the graph, treatment is specified with respect to whether firms' home countries (jurisdictions where firms patents are active) implemented the Enforcement Directive. Across specifications the coefficient for medium-sized firms is largest and statistically significant. While the coefficient of small firms is also positive, sizable and (partially) significant, both coefficients for large firms are very small and insignificant.[20] Results suggest that it is clearly not large firms which account for the main findings. Instead, effects are driven by rather small firms, whereas effects are most pronounced for medium-sized firms.

- Insert Figure 9 here -

Next, we test the complementary role of tangible assets, particularly in the context of firm size. In general, it is fair to assume that the amount of tangible assets serves as a complement for the use of intangible property for attracting loans. For example, reflecting the importance of tangible assets in our setup, in baseline regressions (see Table 7) coefficients of the control variable *tangibility* are persistently positive and statistically significant at the one percent level. An alternative hypothesis could therefore be that high asset tangibility is a necessary condition for firms to deploy their patent portfolios in borrowing activities. More specifically, considering tangible assets in the context of firm size is important because larger, more mature companies have accumulated physical assets which can be deployed in loan contracts more easily. Consistent with this, for sample firms, the share of tangible assets among total assets is significantly lower for small firms (19.9 percent) compared to large firms (25.2 percent). While previous estimates suggest that small and medium-sized firms account for the main results, tangible assets could still be an omitted factor that drives these results. In this case, valuable patent portfolios would not be a sufficient for enhancing firms' debt capacity.

- Insert Table 12 here -

We test this potential channel in a set of regressions displayed in Table 12. For studying this, we determine to which quartile of the average tangible asset ratio distribution in the pre-treatment period each firm belongs. Differentiating among firms with high (Q4), medium (Q2 and 3), and low (Q1) ex ante tangibility shows that positive effects from the baseline regressions hold across

[20] Differences in the magnitude cannot be explained by differences in the size of the dependent variable across size categories. While smaller firms indeed have higher debt-ratios (16.2 percent) compared to large firms (14.5 percent), this difference (1.7 percentage points or 12.2 percent) is small enough to directly compare the coefficients. For example, the coefficients of small and medium-sized firms are between five and eighteen times the size of large firms coefficients.

categories, but are only statistically significant for firms with high or medium tangible intensive firms (Panel A, Columns I-III). To test whether this effect is persistent, we also estimate regressions on all firms and include triple interaction terms in which we multiply the original interaction term with a dummy equal to one for firms that have particularly high (Column V), low (Column VI), and both dummies (Column VII), or zero otherwise. While coefficients on high (low) triple interaction terms are positive (negative), none of the estimates are statistically significant. This suggests that if you have more or less tangibles than firms from the center of the distribution does not have an additional effect on debt ratios. Hence, our main results appear to be driven by firms' value of patents not by complementary other assets.

However, this results do not exclude the possibility that for small and medium-sized firms, asset complementarity is important. We therefore repeat the analysis by splitting the sample according to firms with pre-treatment average employee head counts of below 500 (Panel B) and above 500 (Panel C). There are two main insights to this. First, confirming previous results (i.e. Figure 9) effects for small and medium-sized firms are positive and statistically significant, while being small and statistically not different from zero for large firms. Second, for the sample of relatively smaller firms, estimates follow a very similar pattern as obtained from estimates on all firms (Panel A). Importantly, this suggests that valuable patent portfolios are not only a necessary but also a sufficient aspect for explaining our main results. The size of the negative coefficients on the the triple interaction terms of firms with low ex ante tangibility (Columns VI and VII in all three panels) and the insignificant results on subsamples those firms (Columns III in all three panels), provide suggestive evidence that firms with particularly few tangible assets might not benefit from valuable patent portfolios as much as more tangible asset intensive firms. This is generally consistent with the notion of a complementary use of both, tangible assets and patents.

4.4 Heterogeneity across industry-, firm-, and patent features

This section exploits heterogeneous effects across different subsets of firms other than those related to firm size. This has two main reasons. First, it is reasonable to assume that firms are not affected in a uniform pattern. Essentially, we expect that the effects of patenting on leverage depend on factors that lie outside the scope of patent portfolio value. Testing specific characteristics thus serves as plausibility analysis for our main results. Second, one important contribution of our analyses is to provide a more comprehensive view on the relationship between patenting and debt financing. Exploring the full depth of our dataset, we provide valuable insights on the determinants of this relationship by assessing differentiated effects across firms, industry, and patent characteristics.

4.4.1 Industry characteristics: tech versus non-tech firms

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, their information content can be related more directly to firms' future economic prospects. For example, Loumioti (2012) shows that borrowers' reputation positively affects their ability to deploy intangible assets for attracting loans. Hence, it should be more likely for patenting to attract debt, if it is a rather common (i.e. renowned) practice in a firm's business environment and vice versa.

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 knowledge-intensive or service-oriented sectors it seems more appropriate seeking protection via other property rights, such as trademarks.

Descriptive statistics displayed in Table 13 illustrate differences in patenting and financing 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. Reassuringly, patenting costs do not differ per patent but the larger patent portfolios require higher maintenance costs leading to significantly higher total annual patenting costs. These values evidently mirror a higher patenting propensity of tech firms relative to firms from non-tech sectors. Tech firms appear more restricted in their access to external funding, expressed by lower debt-ratios and RZ-scores.

- Insert Table 13 here -

To test whether effects are more pronounced in patenting-intensive sectors, Table 14 displays a set of repeated regression estimations. We split the sample according to whether firms belong to the tech sectors (Columns I-IV) or not (Columns (V-VIII) following the sectoral classification of Eurostat (2018).[21] For tech firms, the coefficients of interest are large and statistically significant across specifications. Estimates are larger compared to our baseline setup. In contrast, for non-tech firms results are not as consistent. Most estimates are substantially smaller or lack explanatory power in terms of statistical significance.[22] Our findings therefore confirm observations from previous literature and provide further ground for the validity of our main findings. Hence, results confirm that the positive effect of patenting on firms' debt capacity disproportionally applies to firms located in industries with high patenting propensity.

- Insert Table 14 here -

4.4.2 Firm characteristics: financing constraints

In addition to this, it is reasonable to expect heterogeneous effects arising from firm-level characteristics. Specifically, theory suggests that shocks to external funding have more pronounced

[21] See Table IA14 in the Internet Appendix A for a detailed definition of tech sectors.

[22] The point estimates for the standard capital structure determinants (not displayed) are stable across these industries suggesting that variation in patenting is not driven by these effects arising from these covariates. In undisplayed output tables, we find that estimates are robust to changes in the model specifications equivalent to the robustness tests displayed in Tables IA8 and IA9 (Internet Appendix A).

effects if financing frictions are present (e.g. Holmström and Tirole 1997). We thus expect effects to be stronger for firms facing relatively higher financing constraints.

Because literature shows that there is not an unambiguous method of quantifying financial 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 (Freixas and Rochet 2008). We therefore suggest that publicly listed firms are less likely to be financially constrained.[23] Following this, the positive effects of patent portfolios on firms' debt capacity should be disproportionately high for 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 IA15 (Internet 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 smaller but also lack statistical significance. Hence, results 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.

Because stock market participation is - given our broad sample - a rather specific measure to determine financing constraints, we want to use alternative methods for the quantification of financing constraints. Often, firm-level constraint indices rely on information that are only available for large public firms, such as bond market ratings or dividend payouts. Because our sample consists of mainly small and medium-sized firms, we cannot use several of these measures. We therefore use two other measures that help us approximating whether a firm is financially constrained which are both applicable for a broad range of firms.

The first measure 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% 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 grow and become more mature.

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 the respective score

[23] This notion is confirmed in our data. For example, bank debt ratios for private firms are significantly higher than those of listed firms in our sample (25.0% versus 16.3%, t-value 19.893).

in the year the treatment first occurs.[24] 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 15 here -

Table 15 displays regression estimates explaining firms' debt ratios on split samples according to whether firms are considered as constrained (Columns I-III) or not (Columns IV-VI) prior to the treatment. 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 highly statistically significant for the respective subset of constrained firms. For unconstrained firms, results are rather ambiguous. In the first specification (Panel A), none of the estimates is statistically different from zero. In the second specification (Panel B), results are either equivalent in magnitude and statistical significance or smaller and insignificant, depending on the exact specification. While we therefore cannot entirely neglect that unconstrained firms partially benefit from patenting to attract debt financing, effects are robust and much stronger for constrained firms. Hence, similar to the results regarding firms' stock market participation, this suggests that the positive effect of a valuable patent portfolio is disproportionately high for firms that are limited in their access to financial resources.

4.4.3 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. An important characteristic is the ability to redeploy the patent- because of its close link to the commercial value of a patent. Fischer and Ringler (2014) argue that patents have a particularly high potential to be used in loan contracts if they can be redeployed in case of default to practicing entities. The net present value and, hence, the liquidation value of these patents should be particularly high.

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 liqui-

[24]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.

dation 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 technological breadth, we try to answer this theoretical ambiguity by an empirical analysis.

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

- Insert Table 16 here -

Table 16 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 coefficients vary both in terms of size and statistically significance. While coefficients on the subset of broad patent portfolios are large and highly significant, coefficients on specific patents are much smaller and statistically not different from zero.

Despite these differences, these results do not provide conclusive evidence on the relevance of patent portfolios' scope for our main results. The classification into broad patents by just regarding whether they refer to at least two technology classes is rather vague. We therefore go one step further by splitting the subsample of firms ex ante broad portfolios into equally sized quartiles according to their location 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 IA9 (Internet 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 (27.490 and 43.775 versus 14.802 and 1.884) and statistically significant. Hence, this detailed assessment suggests that the relationship between the portfolio scope and its positive effect on 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.

[25] 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.

4.5 Linking patenting and leverage: the costs of obtaining debt

As a final step in our empirical analysis, we establish one potential link between firms' patent portfolios and their leverage ratios to confirm the increased use in external funding as a reaction to increased patent value. The underlying notion is that both the direct as well as the indirect use of patenting in the context of loan contracts helps reducing borrowing costs. Improved access to finance by patents' signaling of 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.[26] Hence, these proxies tend to overestimate the interest burden that arises from firms' external debt holdings. This measurement issue should lead towards underestimating the effect of patenting on firms' interest rates. Our proposed measures can thus be regarded as a conservative approach.

We conduct a set of descriptive analyses to provide a general overview on the relation between patenting and the costs of obtaining debt. First, we take the differences in means of our interest burden measure to compare firms before and after the treatment (see Table 17). While interest expenses are lower for all firms, this difference is small in magnitude and borderline significant, resembling a 2.4% (or 0.2 percentage points) overall decline. We further distinguish between firms with a high and low ex ante patenting value, i.e. treated and control firms. Now, the decline in interest expenses is not different from zero for unaffected firms, while being large and statistically significant for firms affected by the treatment. The average interest burden for treated firms is 5.2% (or 0.5 percentage points) lower comparing pre- (9.0%) to post-treatment rates (8.5%). This difference is statistically significant at the one percent level and suggests a shift in interest burden only for firms we expect to be affected by the treatment.

- Insert Table 17 here -

To further understand differences between the two groups of firms, Figure 10 displays the size of the patent stock (y-axis) and interest burden (x-axis) of treatment and control group firms during both pre- and post treatment periods. While differing in magnitude, both groups display no significant correlation between the number of patents and their interest expenses in the pre-treatment period - illustrated by an almost horizontal linear fit. More importantly, however, for the post-treatment period this fit shifts for the treated firms, suggesting an increased negative relationship between a larger patent portfolio (of high value) and firms' interest burden. For

[26] Note that because of a relatively high number of missing values for the interest expense variable our sample size becomes much smaller compared to the previous analyses.

control firms, respective slopes remain relatively flat after the treatment (right graph) and suggest no - or if any, a positive - correlation between larger (less valuable) patent portfolios and respective firms' interest expenses. The two descriptive approaches indicate a negative correlation between interest burden and patent portfolio value, particularly in the post treatment phase.

- Insert Figure 10 here -

In a set of repeated regressions, we further test whether these descriptive insights can be confirmed by multivariate analyses. Table 18 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.[27] We further add industry-fixed effects to absorb time-invariant, industry-specific lending conditions.

Equivalent to the analyses in the previous subsection, we repeat estimation from the baseline regression specified in Equation (4) 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 but only at the ten percent level. Findings are consistent across specifications but most of the results lack statistical power.

- Insert Table 18 here -

We therefore conduct an additional analysis, evaluating the timing of the impact to better interpret the effects. We thus investigate the entire lag structure in an event window, equivalent to the lag structure analysis on the baseline estimates. Figure IA10 (Internet Appendix B) plots the coefficients of year dummies relative to the first treatment year (left plot). Here, it is generally the case that coefficients in the pre-treatment period are statistically not different from zero, while turning negative and statistically significant after period t+2. However, when comparing the overall level of coefficients across the entire 13 periods, only a small negative shift is observable. Other than this, the pattern is similar to our previous analysis suggesting that the effect of the policy change gradually expands. In contrast, the right panel shows that for control group firms coefficients remain virtually the equivalent throughout the entire sample period.

Summarizing, we find an overall negative but rather moderate effect of patenting on interest burden. This outcome is potentially driven by the imperfect precision of our measure. For example, our above analyses suggest that treated firms obtain disproportionally *more* external debt after the treatment. Ceteris paribus, this should lead to *higher* interest expenses. Hence, the slightly negative signs imply a decrease in interest expenses despite the increased use of external finance and thus potentially suggests that firms in fact pay lower interest rates on individual loans.

[27]The only exception is the cash flow 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.

5 Conclusion

Agency costs in debt financing increase refinancing costs especially for innovation-intense firms. In this paper, we causally show for a large scale of firms that the value of patent portfolios enhances their debt capacity and results in higher leverage ratios. Estimating patenting value is non-trivial, particularly for small, private companies which comprise the majority of firms both in the real business landscape and in our sample. We utilize distinct institutional features of the European patent system to establish a novel measure on firm-level patenting activities. Particularly, reoccurring patenting expenses enable us to precisely track the size and value of each individual patent within firms' patent portfolios on an annual basis. Our analyses show that the measures are able to explain variation along the entire value distribution of patents. To study this, we employ a unique data set, matching in-depth legal patent data on approximately 100,000 patents with firms' balance sheet information (Amadeus) across several European countries over a 13 year time span.

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. This event marks a plausibly exogenous source of variation in patent protection, allowing us to causally interpret that valuable patent portfolios lead to higher debt-ratios when differentiating among ex ante high and low patenting firms. A one standard deviation increase in patent value leads to an increase in debt-ratios of about 17.7% for the average treated firm. To the best of our knowledge, we are the first to analyze the impact of the actively held stock of patents on financing 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 patent filings. Importantly, we show that results are robust to analyzing a matched sample of patenting and non-patenting firms.

Several additional tests confirm that our results are not driven by subsequent or preceding events occurring during our sample time frame, most importantly the financial crisis in 2008. Additionally, we document heterogeneous treatment effects across industry-, firm-, and patent characteristics which serve not only as plausibility tests but also highlight important differences among these characteristics. For example, we show that results cannot be attributed to large firms but it is rather small private firms that predominantly drive results. Consistent with our identification strategy, financially constrained research-intensive firms particularly benefit from high patent values for obtaining debt. In a final step, we investigate how more valuable patent portfolios lead to a lower interest burden and thereby enhance firms' debt capacity.

Our results provide valuable implications from both a governmental and a managerial perspective. First, we are able to quantify patent value for a broad set of firms, demonstrating the potential for innovation-oriented firms to utilize their intellectual property for attracting debt.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: Descriptive statistics on patenting measures

	Citations (per patent)	Total citations (portfolio)	Generality index	Patent cost (per patent)	Patent stock (total)	Patent stock (normalized total)
Mean	3.23	24.48	0.15	1,505.94	72.30	0.031
Std. dev.	3.70	132.20	0.18	987.63	357.79	0.078
Percentiles						
p1	0	0	0	70	1	0.0003
p5	0	0	0	198.36	1	0.0005
p10	0	0	0	338.33	2	0.0009
p25	1	1	0	713.31	4	0.0024
p50	2	5	0.07	1,400.93	19	0.0092
p75	4.33	14	0.25	2,081.44	42	0.0238
p90	7.50	39	0.44	2,625.53	116	0.0643
p95	10.13	74	0.50	3,350.48	224	0.0128
p99	20	343	0.66	4,729.07	950	0.4222

Notes: This table presents descriptive statistics comparing several value-relevant patenting characteristics from our main sample. Column I (II) contains the average (total) number of citations received within the first eight years after patent application for firms' patent portfolio. Column III contains respective average values of the patent generality measure which is a concentration index on the industry classes of citations received. The last three columns contain variants of our patent measure. Column IV contains the costs per patent in firms' patent portfolios. Column V contains the patent stock size as defined in Equation (1). Column VI contains the same values normalized on a year-industry level.

Table 2: Patenting costs and its relation to high impact patents

Dependent variable:	Generality index					
Generality index definition:	Top 25 percent		Top 10 percent		Top 1 percent	
	(I)	(II)	(III)	(IV)	(V)	(VI)
Patent costs	0.306^{***}	0.289^{***}	0.463^{***}	0.441^{***}	0.492^{***}	0.471^{***}
	(0.013)	(0.014)	(0.014)	(0.015)	(0.014)	(0.014)
Additional controls:						
Firm-level	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	Yes	No	Yes
Country-Year FE	No	Yes	No	Yes	No	Yes
Country-Industry FE	No	Yes	No	Yes	No	Yes
R^2	0.12	0.14	0.21	0.24	0.23	0.26
Observations	34,210	34,210	34,210	34,210	34,210	34,210

Notes: The table presents estimates explaining the relationship between patent costs and the occurrence of high impact patents. The regression equations are defined in Equation (3). Patenting costs are the industry-year normalized values of firms total patenting expenditures defined in Equation (2). Patent quality refers to the generality index obtained from Hall *et al.* (2001). Here, we do not use the annual average generality value of firms' patent portfolios but instead use the value of the top 25 (Columns I and II), 10 (Columns III and IV), and 1 (Columns V and VI) percent in the firm-year specific generality distribution. Regression include time-varying firm-level controls, i.e. size, share of tangible assets, profitability, and cash flow. Depending on the specification, we also include a set of fixed effects for firms, country-years, and country-industry pairs. 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 3: Summary statistics: financial and patenting variables

Variable	Obs.	Mean	Std. dev.	Min.	Max.
Debt-ratio	44,004	18.413	25.554	0	100
Size	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 flow	48,820	0.126	0.172	0	0.915
Age	49,634	26.7	26.1	1	131
Quoted	51,719	0.053	0.225	0	1
Patents filed (p.a.)	51,719	0.426	3.167	0	144
Patent portfolio size	51,719	4.948	37.113	0	2,684
Active offices (avg.)	51,719	7.689	9.534	0	37
Portfolio age (avg.)	35,523	6.933	4.920	1	20

Notes: The table displays summary statistics on financial and patenting variables. Financial variables are defined in Table 4 including firms' age and a binary variable indicating whether a firm is listed on the stock market ('quoted'). Additionally, firm-level patent information are defined as follows: Patent filings (portfolio size) refers to the number of patents filed (actively held) within a year. Active offices is the number of EPC jurisdictions at which patents are maintained. Portfolio age refers to the number of years all patents of a firm's portfolio have been maintained active. All values displayed are average firm-year observations.

Table 4: Overview capital structure determinants

Category	Variable	Definition	Predicted relation
Dependent variable:	Debt-ratio	$= \frac{\text{long-term debt}}{\text{total assets}}$	.
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 flow	$= \frac{\text{total cash flow}}{\text{total assets}}$	negative

Notes: The table defines of both the main specification of the dependent variable and a set of common capital structure determinants, including their predicted impact on leverage (see e.g. Graham and Leary 2011). These determinants are included in all regressions. If not displayed, their use is indicated by the term '*firm-level*' in the controls footnote of respective output tables.

Table 5: Summary statistics: affected versus control firms

Ex ante patent portfolio value	Mean values: High	Mean values: Low	Difference in means
Debt-ratio (in %)	13.747	16.201	-2.455***
Size	10.387	9.550	0.837***
Profitability	0.085	0.088	-0.003
Tangibility	0.217	0.228	-0.012***
Cash flow-ratio	0.071	0.071	-0.000
Age	32.429	27.852	4.587***
Quoted (in %)	9.521	6.204	3.317***
Patents filed (p.a.)	1.248	0.143	1.105***
Large patent stock	32.217	3.104	29.113***
Active offices (avg.)	12.184	5.346	6.839***
Portfolio age (avg.)	7.527	6.804	0.723***
Patenting costs	28,540.8	3,878.0	24,662.8***

Notes: The table displays summary statistics on firm-level variables comparing mean values for firms with high and low patenting values as defined in Equation (1), i.e. affected and control group firms. Firms above (below) the median value in the year before the treatment occurs are classified as affected (controls). Treatment occurs once at least one jurisdiction in which a patent from a firm's patent portfolio is active implements the Enforcement Directive, i.e. once the treatment measure departs from zero ($Post > 0$). Variables are used as in Table 3, except of the dummy variable '*large patent stock* which equals one (zero) if the firm actively holds at least (less than) five patents. Patenting costs are defined in Equation (2). The last column displays the differences in mean values, where *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table 6: Average debt-ratios: pre- versus post-treatment comparison

Treatment definition		*Before*	*After*	Difference in means
(I) Patent stock value	Affected	12.726	14.683	1.957***
	Control	15.572	16.025	0.453
(II) Patenting costs	Affected	12.985	15.269	2.285***
	Control	15.439	15.541	0.102

Notes: The table presents mean values of affected and control firms both before and after the treatment. First (I), we define whether a firm is affected by the treatment according to the ex ante patent stock value as defined in Equation (1), i.e. number of active patents in all EPC jurisdictions. Second (II), we consider patenting expenses before the treatment as proxy for patent value derived in Equation (2). In both cases, firms above the median value in the year before the treatment occurs are classified as affected. Before and after denote the firm specific pre- and post-treatment period, i.e. once the treatment measure 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 7: Baseline regression: capital structure determinants and patenting

Dependent variable:	Debt-ratio							
Patent value definition:	Patent stock				Patent costs			
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
Affected × Post			2.655***	2.528***			1.534**	2.462***
			(0.715)	(0.816)			(0.719)	(0.823)
Patent value × Post		23.780***				3.513**		
		(7.094)				(1.438)		
Patent value	7.199	-2.374	7.432	7.322	0.320	-0.899	0.368	0.114
	(5.132)	(3.762)	(5.022)	(5.064)	(1.095)	(1.077)	(1.097)	(1.092)
Size	0.956*	0.971*	0.958*	0.967*	0.948*	0.956*	0.960*	0.961*
	(0.523)	(0.523)	(0.522)	(0.522)	(0.523)	(0.523)	(0.522)	(0.522)
Profitability	-5.470***	-5.555***	-5.444***	-5.398***	-5.404***	-5.397***	-5.391***	-5.324***
	(1.947)	(1.947)	(1.952)	(1.953)	(1.951)	(1.954)	(1.950)	(1.947)
Tangibility	15.035***	15.113***	15.019***	15.007***	15.042***	15.047***	14.943***	14.930***
	(2.033)	(2.024)	(2.032)	(2.037)	(2.035)	(2.033)	(2.037)	(2.037)
Cash flow	-11.303***	-11.156***	-11.279***	-11.317***	-11.379***	-11.341***	-11.373***	-11.420***
	(2.019)	(2.017)	(2.022)	(2.020)	(2.024)	(2.025)	(2.025)	(2.021)
Constant	1.585	1.503	0.974	1.045	1.768	1.579	1.310	1.279
	(5.240)	(4.965)	(5.229)	(5.265)	(5.254)	(5.260)	(5.244)	(5.285)
Additional controls:								
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07
Observations	28,868	28,868	28,868	28,868	28,868	28,868	28,868	28,868

Notes: The table presents estimates from regressions explaining the effect of firms' patent portfolio value on their debt ratios. We repeat the regressions for two alternative definitions of patent value, the patent stock (Columns I-IV) and patent costs (Columns V-VIII), using the first lag of the normalized patent value variables. Dependent and firm-level control variables are defined in Table 4. Regressions control for unobserved heterogeneity by including firm- and country-year fixed-effects. In Column II (VI) we interact the patent stock (cost) with our continuous treatment variable as defined in Section 3. Columns III and IV (VII and VIII) follow our main regression specification defined by Equation (4) interacting the treatment indicator based on the pre-treatment patent stock (cost) value of firms with the two alternative measures of treatment. Columns III and VII use the indicator whether the Enforcement Directive is implemented in the firms' respective home country as treatment variable. Here, single coefficients on the treatment variable (*Post*) are dropped because perfect multicollinearity arising from the inclusion of country-year fixed effects. Columns IV and VIII use the variable measuring the fraction of relevant jurisdictions that implemented the directive. In these cases and in Columns II and VI regressions also control for the level of the firm-specific treatment variable (*Post*); coefficients are not reported but statistically not significant from zero. 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: the announcement effect

Dependent variable:	Debt-ratio							
Sample time frame:	Full sample				Pre-treatment			
Patent value definition:	Patent stock		Patenting costs		Patent stock		Patenting costs	
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
Affected × Post A.		1.144*		1.425**		0.287		0.929
		(0.590)		(0.588)		(0.585)		(0.587)
Patent value × Post A.	13.523***		1.768*		5.484		0.987	
	(5.048)		(1.052)		(3.907)		(1.178)	
Patent value	-1.072	6.866	-0.774	-0.021	-2.816	-0.743	-0.239	-0.049
	(5.000)	(5.097)	(1.196)	(1.079)	(4.240)	(3.709)	(1.178)	(1.076)
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	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07
Observations	28,868	28,868	28,868	28,868	17,833	17,833	17,833	17,833

Notes: The table presents estimates from regressions explaining firms' debt ratios in our *placebo* setup. We use the indicator variable $PostA.$, which equals one after the Enforcement Directive was decided upon by the European Parliament and the Council as of April 29$^{\text{th}}$, 2004 and zero otherwise. For consistency, we consider both all sample years (Columns I-IV) and the years only *before* the Enforcement Directive was actually implemented in respective countries (Columns V-VIII). We use the two alternative proxies for patent value, i.e. the patent stock (Columns I-II and V-VI) and patent costs (Columns III-IV and VII-VIII). All remaining specifications are defined as in the tables above and variables are defined in Table 4. 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: Comparing firm-level characteristics of patenting firms with matched control group

	Mean values		
Group:	**Patenting**	**Non-patenting**	**Difference in means**
Debt-ratio (in %)	9.599	8.795	0.804
Size	8.083	8.044	0.039
Profitability	0.131	0.124	0.007
Tangibility	0.125	0.125	0.000
Cash flow-ratio	0.096	0.092	0.004
Age	20.754	20.621	0.133
Quoted (in %)	1.566	1.620	-0.016

Notes: The table displays summary statistics on firm-level variables comparing mean values for patenting and non-patenting firms in our matched sample. The values reflect pre-treatment means of the two groups. Treatment occurs once the treatment measure departs from zero ($Post > 0$). Variables are used as in Table 3. We obtain matching (i.e. non-patenting) firms by using CEM as described in Section 4.2. The last column displays the differences in mean values, where *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table 10: Treatment effect: patenting versus non-patenting firms from a matched sample

Dependent variable:	Debt-ratio				
	(I)	(II)	(III)	(IV)	(V)
Patentee × Post		1.914** (0.847)	1.673** (0.785)	1.537** (0.775)	1.526* (0.781)
Post		0.122 (0.517)	-0.074 (0.480)		
Patentee	0.616 (0.755)	0.573 (0.787)	2.605 (2.024)		
Additional controls:					
Firm-level	No	No	Yes	Yes	Yes
Firm FE	No	No	No	Yes	Yes
Country-Year FE	No	No	No	Yes	Yes
Country-Industry FE	No	No	No	No	Yes
Observations	11,573	10,265	9,226	9,226	9,226

Notes: The table presents estimates from regressions explaining firms' debt ratios on our sample of matched firms. The sample contains both, patenting (treatment) and non-patenting (control group) firms. In Column I, we first regress the indicator *Patentee*, which is equal to one (zero) if a firm belongs to the treatment (control) group patenting, on firms' debt ratios. Column II includes the indicator of the treatment, i.e. a dummy equal to one (zero) for every country-specific year in which the Enforcement Directive is active, as well as the interaction of the two indicators. Column III estimates Equation (5) and further controls for time-varying firm-specific factors, namely the capital structure determinants as defined in Table 4. Columns IV and V additionally control for a set of fixed effects as indicated in the bottom of the table. Here, the single indicator variables are omitted from estimations because of perfect multicollinearity. 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: The financial crisis as alternative mechanism

Dependent variable:	Debt-ratio							
Sample time frame:	Full sample				Excluding post crisis years			
Patent value definition:	Patent stock		Patenting costs		Patent stock		Patenting costs	
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
Affected × Crisis		0.690		0.979*		1.383		0.515
		(0.540)		(0.541)		(1.002)		(0.986)
Patent value × Crisis	9.562***		1.794**		21.717**		1.098	
	(3.665)		(0.885)		(10.215)		(1.841)	
Patent value	4.212	7.123	-0.185	0.222	2.008	4.819	0.123	0.225
	(4.988)	(5.118)	(1.067)	(1.085)	(3.462)	(4.663)	(1.059)	(1.108)
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	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07
Observations	28,868	28,868	28,868	28,868	22,396	22,396	22,396	22,396

Notes: The table presents estimates from regressions explaining firms' debt ratios using the financial crisis as an alternative treatment event. Specifications use a binary indicator (*Crisis*) as a treatment equal to one either if the home country of a firm experiences a recession as defined by Laeven and Valencia (2013) (Columns I-IV) or if the year is post 2008 (Columns V-VIII). In the last four specifications, the sample time frame is truncated by the country-specific post-treatment period, i.e. the period followed by the recession. We further use the two alternative proxies for patent value, i.e. the patent stock (Columns I-II and V-VI) and patent costs (Columns III-IV and VII-VIII). All remaining specifications are defined as in the tables above and variables are defined in Table 4. Displayed time-variant regressors (*Patent value* and *Crisis*) are included 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: Complementarity of tangible assets across firm sizes

Dependent variable:	Debt-ratio					
Subsample (ex ante tangibility)	High (Q75)	Medium (Q25-50)	Low (Q25)	All		
Panel A: All firms						
	(I)	(II)	(III)	(IV)	(V)	(VI)
FI × Exposure	3.131*	2.612**	1.574	2.291**	2.968***	2.823***
	(1.639)	(1.079)	(2.006)	(0.919)	(0.875)	(0.997)
FI × Exp. × Tangibility^{Q75}				0.984		0.468
				(1.605)		(1.638)
FI × Exp. × Tangibility^{Q25}					-2.130	-1.991
					(1.793)	(1.835)
(Obs.)	(7,482)	(15,235)	(6,157)	(28,938)	(28,938)	(28,938)
Panel B: Small and medium-sized firms (<500 employees)						
	(I)	(II)	(III)	(IV)	(V)	(VI)
FI × Exposure	6.146**	3.631**	2.483	3.470***	4.486***	4.037***
	(2.848)	(1.532)	(2.544)	(0.919)	(0.875)	(0.997)
FI × Exp. × Tangibility^{Q75}				2.131		1.584
				(2.818)		(2.872)
FI × Exp. × Tangibility^{Q25}					-2.130	-1.991
					(1.793)	(1.835)
(Obs.)	(3,978)	(8,587)	(4,155)	(16,720)	(16,720)	(16,720)
Panel C: Large firms (>500 employees)						
	(I)	(II)	(III)	(IV)	(V)	(VI)
FI × Exposure	-0.111	1.228	-0.969	0.496	0.997	1.093
	(1.639)	(1.079)	(2.006)	(1.315)	(1.166)	(1.367)
FI × Exp. × Tangibility^{Q75}				0.293		-0.288
				(1.822)		(1.861)
FI × Exp. × Tangibility^{Q25}					-2.497	-2.589
					(2.690)	(2.768)
(Obs.)	(3,504)	(6,648)	(2,002)	(12,154)	(12,154)	(12,154)
Additional controls:						
Firm-level	Yes	Yes	Yes	Yes	Yes	Yes
Firm-FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year-FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents estimates from fixed-effect panel regressions explaining the effect of the Enforcement Directive on firms' debt-to-asset ratios, distinguishing among different degrees of tangibility intensities. Tangibility refers to the fraction of tangible fixed assets over total assets and is calculated based on firms' pre-treatment average values. In Columns I-III, the main specification (Equation 4) is estimated on a sample of firms with high, medium, and low levels of tangible assets during the pre-treatment period. High (low) tangibility refers to firms in the top (lower) quartile of the pre-treatment tangibility distribution. In Columns IV-VI, the full sample is used and we include additional interaction terms that multiply an indicator variable for high (Column IV), low (Column V), and both, high and low (VI), patenting intensities. In Panel A, we use the full sample, while Panel B (C) repeats the equivalent analyses on the subset of ex-ante small and medium-sized (large) firms which are firms with on average fewer (more) than 500 employees during the pre-treatment period. All regressions contain the control variables that are used in the main specification. Standard errors (in parentheses) are heteroscedasticity-consistent and clustered at the firm level. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table 13: The role of firm size in explaining the main results

Dependent variable:	Debt-ratio					
Specifications	Variant 1		Variant 2		Variant 3	
	(I)	(II)	(III)	(IV)	(V)	(VI)
Affected × Post^{T1}	2.129***		2.063**		2.216***	
	(0.800)		(0.842)		(0.826)	
Firm size × Post^{T1}	1.082		1.001		0.052	
	(0.663)		(0.687)		(0.060)	
Affected × Post^{T2}		2.586***		1.418*		2.434***
		(0.710)		(0.729)		(0.713)
Firm size × Post^{T2}		0.922		0.876		0.290**
		(0.777)		(0.785)		(1.437)
Patent value	-0.317	0.151	-0.176	0.337	-0.235	0.130
	(1.098)	(1.082)	(1.105)	(1.099)	(1.093)	(1.078)
Constant	10.470***	10.325***	10.548***	10.584***	10.558***	8.734***
	(0.624)	(0.690)	(0.624)	(0.689)	(0.666)	(1.222)
Additional controls:						
Firm-level*	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year 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	28,827	28,827	28,827	28,827	28,827	28,827

Notes: The table presents estimates explaining the effect of the Enforcement Directive on firms' debt ratio using several different model variable specifications. All regressions are equivalent to those specified in Equation (4) but additionally include an interaction term of firm size with the treatment variable. *Because we include this size parameter we exclude the size control variable (log. assets). Including the parameter does not affect the main results. Estimations use the two treatment specifications that determine whether jurisdictions where firms patents are active (Post^{T1}) or whether firms' home countries (Post^{T2}) implemented the Enforcement Directive. In Variant 1 (Columns I and II) firms are categorized as affected by the treatment if they have an ex ante above median patenting value. The firm size variable is an indicator equal to one (zero) for firms with more (less) than 500 employees. In Variant 2 (Columns III and IV) , firms are categorized as affected according to their ex ante patenting expenses. Variant 3 (Columns V and VI) is equivalent to Variant 1 but uses a continuous size measure, namely firms' average pre-treatment logarithm of assets. All remaining variables are specified as above and defined in Table 4. 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 14: Patenting and debt use across industries: tech versus non-tech firms

Sectors:	**Tech firms**	**Non-tech firms**	
	Mean	**Mean**	**Difference in means**
Patents filed (p.a.)	0.61	0.36	0.25***
Large patent stock	0.14	0.11	0.03***
Active offices (avg.)	8.06	7.69	0.37***
Patent lifespan (years)	6.93	7.03	-0.10
Patenting costs (p.a.)	13,555	10,274	3,281***
Patenting costs (per patent)	1,032	1,074	41
Debt-ratio	13.82	16.67	-2.85***
RZ index	0.24	0.38	-0.14***

Notes: The table compares mean values of observable patent characteristics according to firms belonging to tech-oriented or non-tech sectors as classified by Eurostat (2018). All patent-related variables equivalent to those specified as in Table 5 with the exception of patenting costs which equals the average firm-level patenting costs either per year (*p.a.*) or per patent. The RZ index is measured on the firm level by $(Capex - CF)/CF$, with total of fixed assets expenditures, $Capex$, and the cash flow, CF. 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 15: Industry-level heterogeneity: tech versus non-tech firms

Dependent variable:	Debt-ratio							
Sectoral affiliation:	Tech sectors				Non-tech sectors			
Patent value definition:	Patent stock		Patenting costs		Patent stock		Patenting costs	
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
Affected × Post		2.563**		2.274**		2.132		2.632**
		(0.925)		(0.985)		(1.360)		(1.273)
Patent value × Post	34.186***		4.551**		11.607*		2.045	
	(10.307)		(1.927)		(7.786)		(2.129)	
Patent value	-3.560	12.700	-2.185	-0.825	-0.846	3.481	0.593	1.046
	(7.899)	(11.124)	(1.624)	(1.662)	(3.331)	(3.253)	(1.634)	(1.515)
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	0.08	0.08	0.07	0.07	0.07	0.07	0.07	0.07
Observations	17,400	17,400	17,400	17,400	11,468	11,468	11,468	11,468

Notes: The table presents estimates from panel regressions explaining debt-ratios of sample firms. We repeat regressions from baseline estimations as displayed in Table 7 (specifically specifications from Columns II and IV when using patent stock and VI and VIII when using patent costs) but split the sample in the subgroups according to their industry-specification: Only tech firms (Columns I-IV) and non-tech firms (Columns V-VIII) as defined by Eurostat (2018). All remaining specifications remain the same (see Table 5). 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 16: 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)	(VII)	(VIII)
Affected × Post		3.122***		3.968***		2.043		1.029
		(1.189)		(1.280)		(1.549)		(1.651)
Patent value × Post	24.015**		4.663*		9.187		4.071	
	(11.616)		(2.517)		(12.556)		(3.294)	
Patent value	-7.347	4.585	-2.588	-1.455	8.488	13.715	-1.241	-0.359
	(10.508)	(8.393)	(2.024)	(1.830)	(8.217)	(9.764)	(1.852)	(1.651)
R^2	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09
Observations	6,039	6,039	6,039	6,039	7,046	7,046	7,046	7,046
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)	(VII)	(VIII)
Affected × Post		4.179***		2.147*		1.428		2.141*
		(1.294)		(1.244		(1.057)		(1.022)
Patent value × Post	23.675***		6.614***		23.962**		1.303	
	(8.614)		(2.324		(11.866)		(1.965)	
Patent value	-4.659	6.367	-3.113**	-1.240	-0.734	7.772	0.556	0.112
	(5.195)	(6.586)	(1.497)	(1.531)	(5.648)	(8.050)	(1.483)	(1.474)
R^2	0.06	0.06	0.06	0.06	0.09	0.09	0.09	0.09
Observations	10,409	10,409	10,409	10,409	16,271	16,271	16,271	16,271
Additional controls both in Panel A and B:								
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

Notes: The table presents estimates from regressions explaining firms' debt ratios. We repeat regressions from baseline estimations as displayed in Table 7 (specifically specifications from Columns II and IV when using patent stock and VI and VIII when using patent costs) but split the sample according to their degree of being financially constrained. Panel A approximates financing constraints on the firm level by the RZ-score as defined by Rajan and Zingales (1998) measured at the firm-specific year the treatment begins. The RZ index equals $(Capex - CF)/CF$, with $Capex$ being the total of fixed assets expenditures and CF. Higher values reflect higher dependence on external funding. 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-IV) or not (Columns V-VIII). Columns I-II and V-VI (III-IV and VII-VIII) use the ex ante patent stock (costs) intensity as treatment definition. All remaining variables and regression specifications follow those in the baseline setup. 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 17: Patent-level heterogeneity: broad versus specific patent portfolios

Dependent variable:	Debt-ratio							
Patent scope:	Specific		Broad		Breadth-Quartiles			
	All		All		*Q4*	*Q3*	*Q2*	*Q1*
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
Affected × Post		1.384 (1.766)		2.443** (1.209)				
Patent value× Post	19.090 (18.794)		25.369*** (8.838)		14.802 (16.044)	27.490** (11.017)	43.775*** (12.683)	1.884 (8.800)
Patent value	-0.233 (10.090)	11.588 (7.039)	-0.205 (4.469)	7.867 (6.456)	3.879 (9.960)	-8.844 (5.947)	3.687 (4.331)	11.679 (7.121)
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	0.10	0.10	0.08	0.07	0.10	0.14	0.11	0.10
Observations	5,814	5,814	11,482	11,482	2,978	2,845	2,925	2,734

Notes: The table presents estimates from panel regressions explaining debt-ratios of sample firms. We repeat the baseline regressions (see Table 7) but split the sample in the subgroups according to the scope of the pre-treatment patent portfolio: specific and broad patent portfolios. Patent portfolios are defined as specific (Columns I-II), if they refer to only one distinct technology class. They are defined as broad if they refer to more than one technology class (Columns III-IV). In Columns V-VIII, we further split the sample of firms with a broad pre-treatment portfolio into four equal sized bins reflecting the location in the pre-treatment originality-index distribution of broad patent portfolios. Originality is measured by a concentration index of IPC4 classes and, hence, lower quartiles reflect broader patent portfolios. Firm-level control variables are defined as specified in Table 4. 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 18: Average interest burden: pre- versus post-treatment comparison

	Obs.	Min.	Max.	Mean		Differences in means
				Before	*After*	
All firms	16,116	0.0009	0.2025	0.0884	0.0864	-0.0021*
Affected	4,983	0.0009	0.2024	0.0901	0.0854	-0.0047***
Unaffected	11,133	0.0010	0.2025	0.0878	0.0871	-0.0007

Notes: The table presents descriptive statistics on firms' interest burden defined as the share of total interest expenses in a given period over the average outstanding long-term debt during the respective period: $int.\,burden_t = ttl.\,int.\,expenses_t / [(lt.\,debt_t + lt.\,debt_{t-1})/2]$. Mean values are displayed for the firm-specific pre- and post-treatment periods. Before (after) denotes the firm specific pre- (post-) treatment period, i.e. once the treatment measure departs from (is equal to) zero. The last column displays the difference between pre- and post-treatment means with *, **, and *** denoting significance at the 10, 5, and 1 percent level, respectively.

Table 19: The costs of debt: Enforcement Directive, patent stock, and interest burden

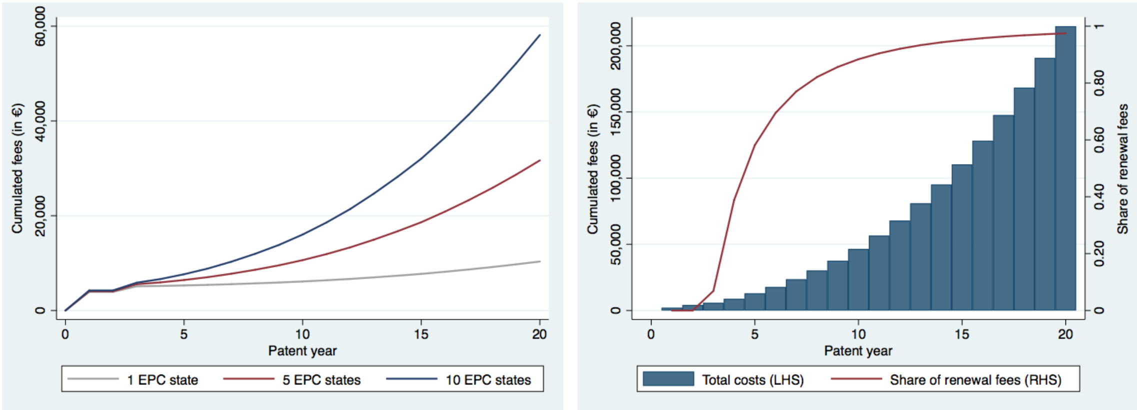
Dependent variable:	Interest burden					
Specification:	Interest expenses to avg. debt-ratio			Logarithm		
	(I)	(II)	(III)	(IV)	(V)	(VI)
Affected × Post			-0.016*			-0.012*
			(0.009)			(0.007)
Patent value × Post		-0.040			-0.029	
		(0.054)			(0.042)	
Patent value	-0.027	0.005	-0.014	-0.019	0.006	-0.008
	(0.034)	(0.034)	(0.035)	(0.026)	(0.027)	(0.027)
Size	-0.015***	-0.016***	-0.016***	-0.011***	-0.012***	-0.012***
	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
Profitability	0.088***	0.088***	0.088***	0.070***	0.070***	0.070***
	(0.021)	(0.021)	(0.021)	(0.016)	(0.016)	(0.016)
Tangibility	-0.078***	-0.076***	-0.076***	-0.061***	-0.059***	-0.059***
	(0.026)	(0.026)	(0.026)	(0.020)	(0.020)	(0.020)
Cash flow	-0.123***	-0.123***	-0.123***	-0.097***	-0.097***	-0.097***
	(0.024)	(0.024)	(0.024)	(0.018)	(0.018)	(0.018)
Constant	0.348***	0.219***	0.220***	0.281***	0.187***	0.187***
	(0.058)	(0.058)	(0.059)	(0.046)	(0.046)	(0.046)
Additional controls:						
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.04	0.05	0.05	0.05	0.05	0.06
Observations	19,217	19,217	19,217	19,217	19,217	19,217

Notes: The table presents estimates from regressions explaining firms' interest burden. In Columns I-III we proxy interest rates by dividing overall interest expenses, calculated at the end of the year, by the average debt holdings during the year. To control for outliers we truncate this share at the 99^{th} quartile. In Columns IV-VI we proxy interest rates in the same way but take the logarithm instead of truncating the value by outliers. We first introduce the two base cases (Columns I and IV). Then, we further include the interaction of the continuous patent stock measure with the country-specific treatment dummy equal to one after the implementation of the directive (Columns II and V). In a third specification, we use the interaction of treatment with the binary indicator of whether a firm has a high pre-treatment value of patent stock or not (Columns III and VI). To control for industry-specific borrowing costs, we additionally control for industry-year fixed effects. All remaining variables are specified as above and defined in Table 4 and the regression specification follows previous estimations, i.e. Equation (4). Patent stock and the treatment indicator are included 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.

Figures from the main part:

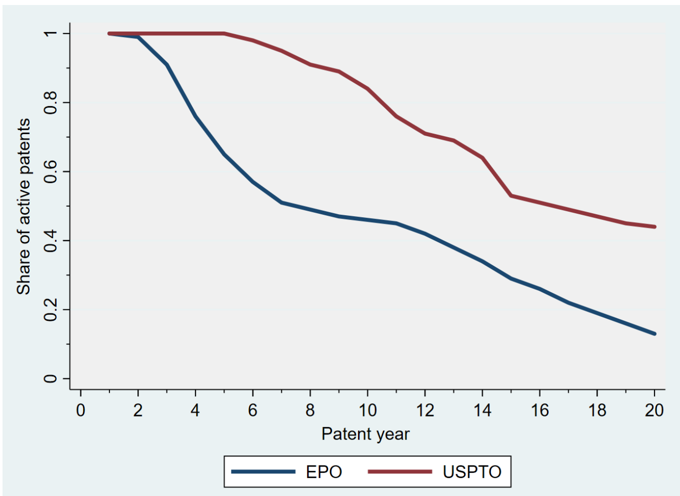
Figure 1: Renewal costs over patent life

Panel A: Panel B:



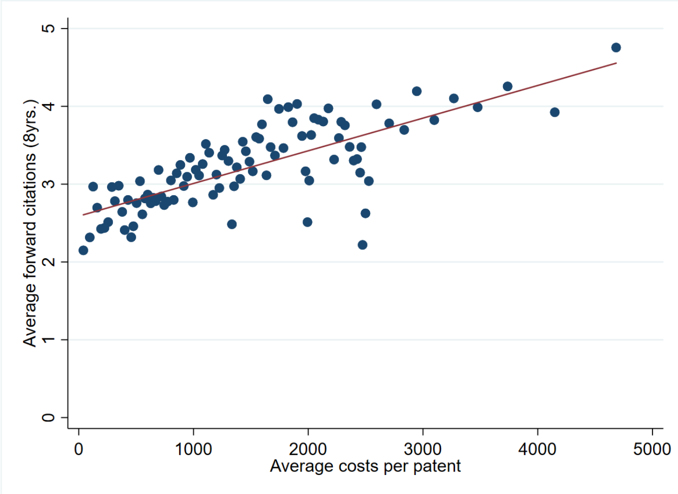
Notes: The two graphs illustrate the renewal structure for patents in EPC member states over the course of their life span. Panel A displays the *average* annual fees necessary to maintain patent protection for each of the maximum 20 years of patent life. These costs include the most common application, grant, and renewal fees. For illustration purposes we consider the average renewal fees per EPC country based on the payment schedule of 2006 (see Table IA3 in the Internet Appendix A). The costs may actually vary depending on which specific jurisdictions are chosen. The lines refer to the number of designated jurisdictions where the patent is renewed, i.e. 1, 5, or 10 jurisdictions, respectively. Panel B plots the *cumulative* amount of fees over the patent life span (blue bars, left axis) and the share of renewal costs among total patenting costs (red line, right axis). Values resemble costs for an *example firm* which holds 5 patents across 8 jurisdictions (compare with Table IA4 in the Internet Appendix A). These values are based on sample averages and comprise administrative costs but do not include irregular costs, such as those arising from lawsuits.

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



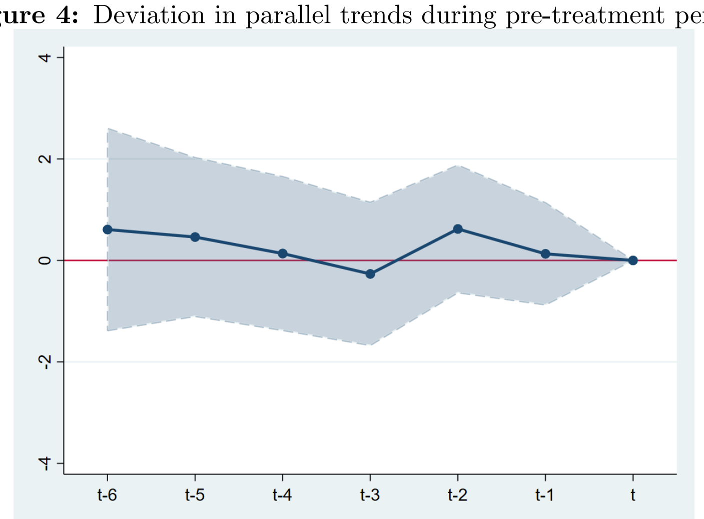
Notes: This figure compares the fraction of granted patent registrations that are still in force for each patent year starting with the year of grant (i.e. 1) until reaching the maximum protection length of 20 years. The reference year is 2010. We differentiate among patents filed at EPO (blue) and at USPTO (red), 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. Own illustration based on data from IP5 (2018).

Figure 3: Relating patent citations to patenting costs



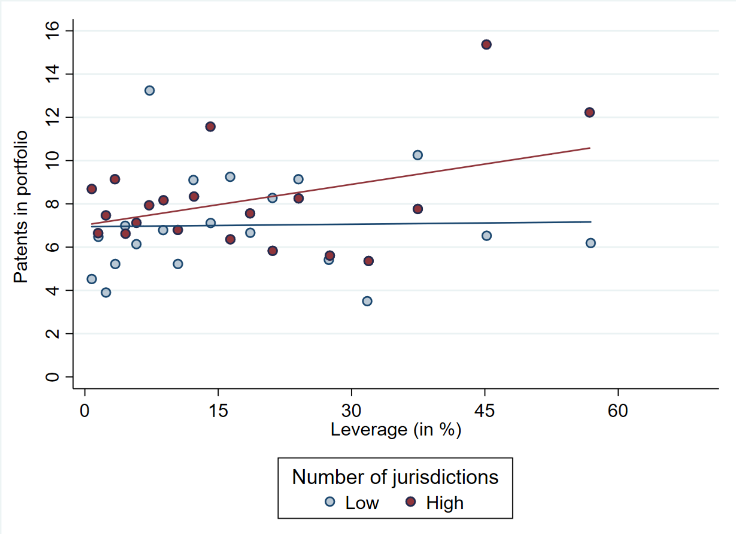
Notes: This binned scatter plot relates the average number of forward citations received by a patent in a firms' patent portfolio to the average costs of patents in the same portfolio. The number of bins is set to 100.

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



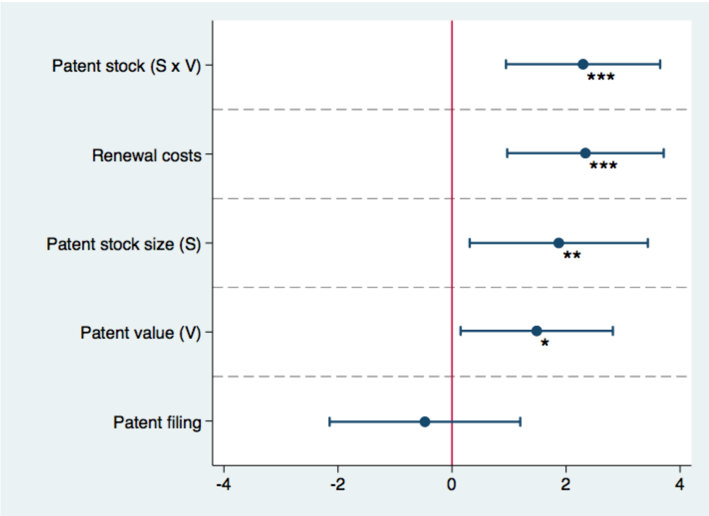
Notes: This figure plots coefficients of the interaction terms of year dummies with the indicator whether the firm is considered as an ex ante high patenting firm. Year dummies indicate the years before the implementation of the Enforcement Directive in the respective country. High (and low) patenting is defined by median split according to the pre-treatment patent stock measure as specified in Equation (1). The regression follows the setup of our main specification from Equation (4). Thus, coefficients capture the difference in the paths between treated and control firms in the difference-in-differences setup during the pre-treatment period. The shaded area marks 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. The implementation year, t, is the base year.

Figure 5: Binned scatterplot: portfolio size and leverage by patent value



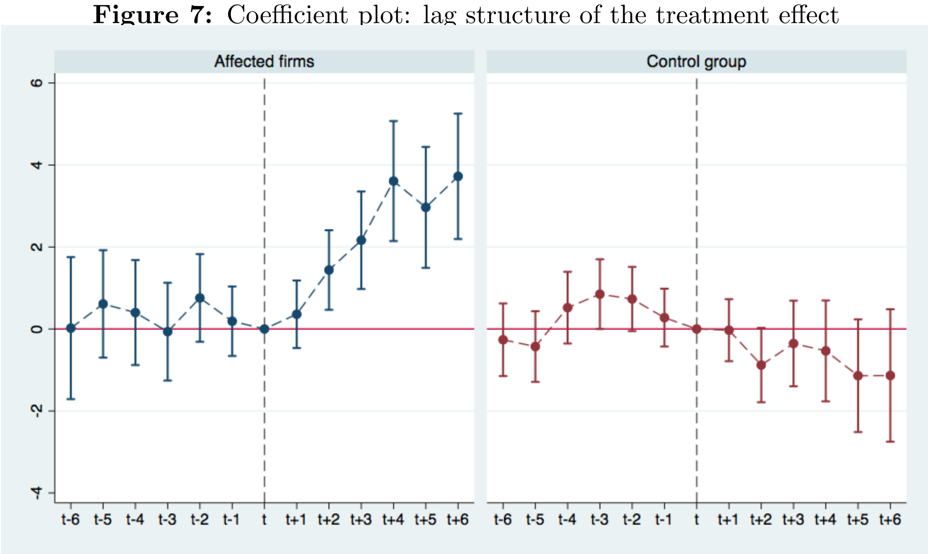
Notes: This binned scatterplot relates the number of actively held patents (y-axis) to leverage ratios (x-axis) of sample firms. The plot displays the values and the linear fit according to firms' patenting value, specified as patent stock and defined in Equation (1). We split the sample according to high and low depending on whether the average patent value of a firms' patent portfolio is above or below the overall median value. The number of bins in each subgroup is set to 20.

Figure 6: Patent portfolio values and leverage: pre- and post treatment comparison



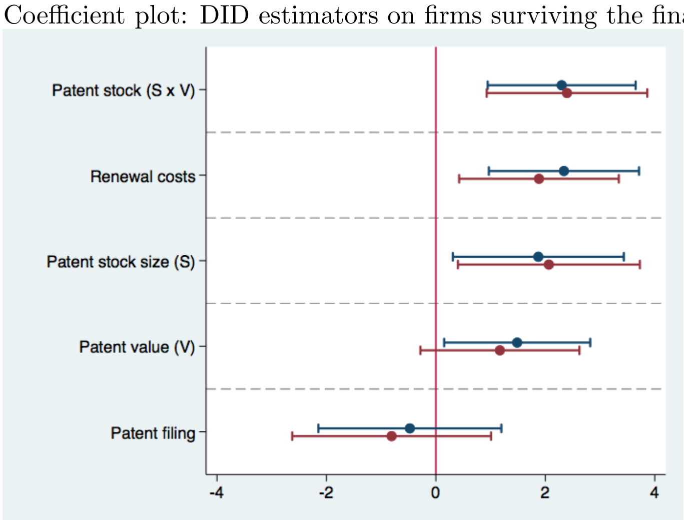
Notes: This figure plots coefficients of the difference-in-differences estimators obtained from the regression specified by Equation (4). In the first two rows, we consider our main treatment measures indicating firms with an above median patent value prior to treatment as defined by Equations (1) and (2) respectively. In the third and fourth row, we split the patent stock variable into its components. Firms are classified as treated with an ex ante above median patent stock size (Row 3) or number of active jurisdictions, i.e. the average value of patents, (Row 4). In the last row, we define a firm as treated, if it filed at least one patent in the period preceding initial treatment. Treatment refers to the share of relevant jurisdictions that implemented the Enforcement Directive. Whiskers span the 90 percent confidence intervals. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Figure 7: Coefficient plot: lag structure of the treatment effect



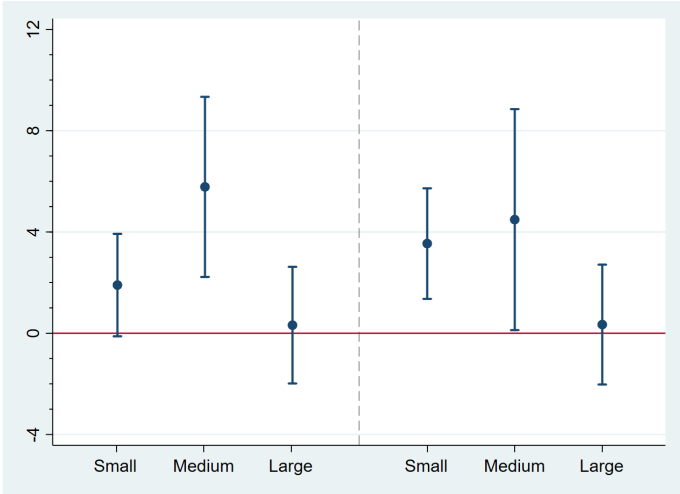
Notes: These figures depict the timing of patent portfolios' effect on leverage before and after the adoption of the Enforcement Directive both for the treatment (left graph) and control group firms (right graph). The plot displays the coefficients, $\alpha^{Tr}_{\tau_i}$ (left graph) and $\alpha^{C}_{\tau_i}$ (right graph), of the two individual regressions ($s \in [Tr, C]$): $Debt\text{-}ratio_{it} = \vartheta_i + \eta_{ct} + \alpha^s(Firm^s_i \times Enforcement_{t+\tau_i}) + \beta CS_{it} + u_{it}$, 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. $Firm^s_i$ 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 $s = C$), that is whether the firm belongs to the treatment or control group, and zero otherwise. The remaining variables are specified in Table 4. Whiskers span the 90 percent confidence intervals.

Figure 8: Coefficient plot: DID estimators on firms surviving the financial crisis



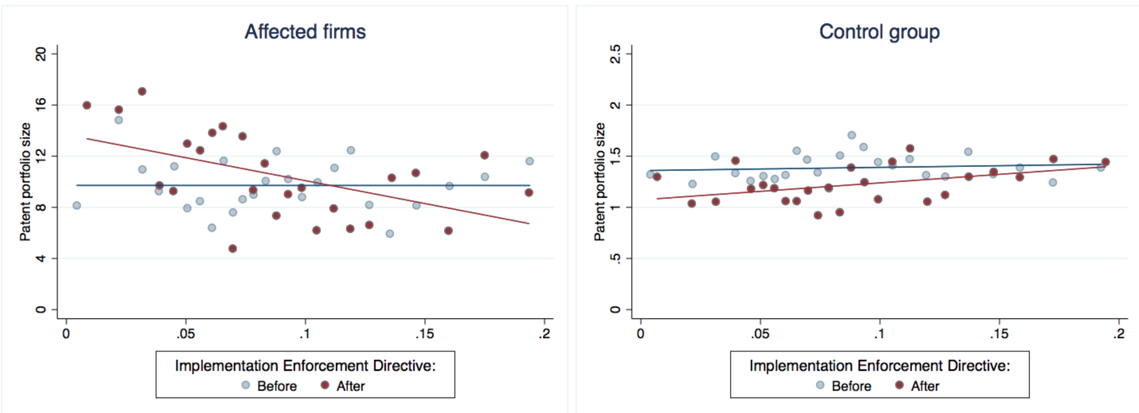
Notes: This figure plots coefficients of the difference-in-differences estimators obtained from the regression specified by Equation (4). All specifications are equivalent to those defined for Figure (5). The only difference is that we distinguish between all firms (blue) and those we assume surviving the financial crisis (red). We define 'survivors' as firms that appear at least five times in the dataset in the years after the onset of the financial crisis in 2007. Whiskers span the 90 percent confidence intervals.

Figure 9: DID estimators on firm size categories



Notes: This figure plots coefficients of the difference-in-differences estimators explaining the effect of the Enforcement Directive on firms' debt ratio according to different firm sizes obtained from the regression specified by Equation (4) using different subsamples and two specifications of the treatment variable. The sample is split according to firms sample size defined by the average number of employees during the pre-treatment period between 2000 and 2004. Firms with, on average, less than 100 employees are categorized as small, firms with 100-500 employees are categorized as medium-sized, and firms with at least 500 employees are categorized as large, respectively. All specifications use the interaction of treatment with the binary indicator of whether a firm has a high pre-treatment costs. The treatment specification in the left (right) plot specifies whether respective firms' home countries (jurisdictions where firms patents are active) implemented the Enforcement Directive. To control for industry-specific borrowing costs all regressions control for industry-year fixed effects. Whiskers span the 90 percent confidence intervals.

Figure 10: Binned scatterplot: portfolio size and interest burden



Notes: These binned scatterplots relate the number of active patents (y-axis) to firms' interest burden (x-axis). The plots display the values and the linear fit before and after treatment separately. Before (after) denotes the firm specific pre- (post-) treatment period, i.e. once the treatment measure departs from (is equal to) zero. Graphs are plotted both for affected (left graph) and control group (right graph) firms. Treated (control) firms have an above (below) median ex ante patent stock value as defined by Equation (1). We exclude all estimated interest rates that are implausibly high, i.e. above 0.2. The scatterplot controls for country-year fixed effects and capital structure determinants specified above and thus follows Equation (4). The number of bins in each subgroup is set to 25.

INTERNET APPENDIX

Internet Appendix A: Tables (IA1 - IA16)

Table IA1 (Panel A): Renewal fee schedule Europe (in Euro as of December 2006)

EPC member state	Y1	Y2	Y3	Y4	Y5	Y6	Y7	Y8	Y9	Y10
Albania*	41	49	65	73	81	97	114	138	162	203
Austria	0	0	70	150	150	150	270	270	270	500
Belgium	0	0	30	45	60	75	90	110	130	150
Bulgaria	0	0	8	26	51	77	102	153	205	256
Croatia*	0	0	44	50	58	69	85	102	111	165
Cyprus	0	0	15	18	23	29	35	41	47	53
Czech Rep.	35	35	35	35	71	71	71	71	106	141
Denmark	67	67	67	147	168	188	215	241	275	308
Estonia	26	26	64	77	96	115	134	153	179	205
Finland	150	150	150	125	140	165	200	235	265	300
France	0	35	35	35	35	150	150	150	150	150
Germany	0	0	70	70	90	130	180	240	290	350
Greece	0	0	0	0	54	70	84	98	114	134
Hungary	181	202	302	302	384	384	423	423	465	465
Iceland	38	38	38	56	56	72	72	90	90	111
Ireland	0	0	60	90	114	134	150	176	194	220
Italy	0	0	0	0	60	90	120	170	200	230
Latvia	0	0	85	128	142	149	171	213	256	320
Liechtenstein	0	0	0	0	64	64	199	199	199	199
Lithuania	0	0	81	93	116	139	162	185	209	232
Luxembourg	0	0	29	37	47	59	74	89	104	118
Malta*	0	0	35	47	58	70	82	93	105	116
Monaco	16	18	29	31	50	70	83	96	110	123
Netherlands	242	279	318	353	390	443	492	541	581	624
North Macedonia*	0	0	13	16	20	23	26	30	33	49
Norway*	68	68	68	137	137	137	236	236	236	354
Poland	69	69	69	26	54	67	77	90	116	141
Portugal	30	37	41	50	61	80	93	108	130	162
Romania	0	0	150	160	180	200	220	240	260	280
San Marino*	0	0	0	70	70	70	70	140	140	140
Serbia*	0	0	85	103	121	145	169	193	218	242
Slovakia	0	0	40	43	46	51	57	73	94	121
Slovenia	0	0	30	35	42	50	60	70	80	110
Spain	0	0	21	27	51	75	99	124	148	172
Sweden	0	27	38	76	97	119	146	173	206	244
Switzerland	0	0	0	0	64	64	199	199	199	199
Turkey	0	131	144	157	169	181	197	206	223	231
United Kingdom	0	0	0	0	73	103	132	161	191	220
EPO	0	0	400	425	450	745	770	800	1,010	1,065

Notes: The table displays hand-collected annual renewal costs across EPC member states stipulated in the schedule of fees by the EPO as of December 31st, 2006. Fees are originally denoted in the national currency. Here, all fees are converted to Euro values using the an average annual exchange rate (Deutsche Bundesbank 2020) for those countries that did not have the Euro as official currency in 2006. The payment schedule illustrates the different fees both across jurisdictions and across patent life. For San Marino and North Macedonia we use 2011 values because of data availability. For Italy, we use 2009 values, because the country temporarily expelled renewal fees between Jan. 1, 2006 and Jan. 1, 2007. Countries marked with * were no EPC member states in 2006. This table (Panel A) displays renewal fees for patent years 1 until 10.

Table IA1 (Panel B): Renewal fee schedule Europe (in Euro as of Dec. 31st 2006)

EPC member state	Y11	Y12	Y13	Y14	Y15	Y16	Y17	Y18	Y19	Y20
Albania	244	244	244	244	244	244	244	244	244	244
Austria	500	500	850	850	850	1,400	1,400	1,400	1,400	1,400
Belgium	170	190	220	250	285	320	355	395	435	475
Bulgaria	307	358	409	460	511	562	614	655	767	869
Croatia	234	248	275	289	317	399	482	633	798	950
Cyprus	59	70	82	94	105	123	140	158	176	193
Czech Rep.	212	282	353	424	494	565	636	706	777	847
Denmark	342	375	409	442	483	523	563	603	644	684
Estonia	243	281	320	358	403	447	492	537	582	626
Finland	350	400	450	500	535	585	645	705	755	805
France	300	300	300	300	300	600	600	600	600	600
Germany	470	620	760	910	1,060	1,230	1,410	1,590	1,760	1,940
Greece	154	184	214	242	272	322	358	392	430	472
Hungary	484	484	505	505	525	525	544	544	565	565
Iceland	111	142	142	178	178	221	250	284	318	352
Ireland	242	265	285	311	335	356	382	408	438	468
Italy	310	410	530	600	650	650	650	650	650	650
Latvia	320	320	320	320	320	427	427	427	427	427
Liechtenstein	199	199	199	199	199	199	199	199	199	199
Lithuania	290	290	290	290	290	348	348	348	348	348
Luxembourg	130	145	160	175	190	205	220	235	250	270
Malta	128	140	151	163	175	186	198	210	221	233
Monaco	151	179	206	236	267	274	282	288	308	326
Netherlands	667	726	835	897	944	992	1,057	1,106	1,106	1,106
North Macedonia	66	82	99	115	131	148	164	181	197	214
Norway	354	354	485	485	485	597	597	597	734	734
Poland	167	193	218	244	270	295	321	347	372	398
Portugal	190	216	259	303	346	389	432	476	519	562
Romania	300	320	340	370	400	500	500	500	500	500
San Marino	140	270	270	270	270	400	460	530	600	650
Serbia	290	338	387	435	483	532	580	628	677	725
Slovakia	148	175	202	229	256	296	337	377	418	458
Slovenia	154	200	234	274	310	390	510	654	870	1,100
Spain	208	245	281	318	354	403	451	499	548	596
Sweden	271	292	309	330	357	384	411	438	466	487
Switzerland	199	199	199	199	199	199	199	199	199	199
Turkey	248	274	298	323	349	387	429	462	504	543
United Kingdom	249	279	308	337	367	396	440	484	528	587
EPO	1,065	1,065	1,065	1,065	1,065	1,065	1,065	1,065	1,065	1,065

Notes: The table is the continuation of Table A4 (Panel A) and displays renewal fees for patent years 11 until 20.

Table IA2: Calculation of annual fees - an example

Example firm in 2006 (based on sample averages):	
Patents in portfolio:	5
Number of jurisdictions:	8
Average portfolio age:	11

Patent year	**Cost factors**	**Annual costs (in €)**	**Cumulated costs (in €)**	Avg. renewal costs per country (in €)
1	Application fees*	2,082	2,082	-
2	Application fees*	2,082	4,164	-
3	Grant and renewal fees	1,640	5,804	-
4	Renewal fees	3,037	8,841	76
5	Renewal fees	4,082	12,923	102
6	Renewal fees	4,799	17,723	120
7	Renewal fees	5,831	23,554	146
8	Renewal fees	6,656	30,209	166
9	Renewal fees	7,463	37,672	187
10	Renewal fees	8,779	46,451	219
11	Renewal fees	10,107	56,557	253
12	Renewal fees	11,358	67,916	284
13	Renewal fees	13,051	80,966	326
14	Renewal fees	14,178	95,145	354
15	Renewal fees	15,273	110,418	382
16	Renewal fees	17,917	128,335	448
17	Renewal fees	19,293	147,627	482
18	Renewal fees	20,737	168,364	518
19	Renewal fees	22,451	190,815	561
20	Renewal fees	24,003	214,818	600

Notes: The table illustrates patenting costs of an average sample firm. Costs are based on the EPO payment schedule as of 2006 (see Table IA3 in the Internet Appendix A). For simplicity, we assume a firm files her patents at EPO via international filing and moves the patent to the national phase after grant, i.e. on average in the fourth year after application. Costs arising during the pre-grant period are application and grant costs. Application costs comprise examination fees, translation fees, international search and filing fees. Grant costs comprise the grant and designation fees. During the third year, we assume the firm to pay renewal fees at EPO, while moving to the national phase and thus paying fees to individual national offices beginning with year four. The table displays both annual and cumulated costs as well as the average cost to renew *one* patent at *one* jurisdiction. Jurisdictions here refer to all possible designation countries and include all EPC countries as of 2019. With average patent renewal expenses (of one patent in one jurisdiction) for the years 4 to 6 of 298 Euro, this scheme is consistent with previous literature. For example, using a reference fee schedule from 2003, Harhoff *et al.* (2009) estimate average patent renewal fees to amount to 278 Euro. *Note, in some jurisdictions renewal fees already apply also during the first two years. However, because we regard EP patents only, we expect them to migrate to the national phase (where these renewal fees during the first years apply) only after the third year, i.e. the year of grant.

Table IA3: 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 sample across countries, including the percentage as share of the total number of observations.

Table IA4: 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, E - Electricity/gas and water supply	436	(0.84)
F - Construction	1,965	(3.80)
G - Wholesale and retail trade	6,942	(13.42)
H - Transportation and storage	484	(0.94)
I, R - Accommodation and arts/entertainment	445	(0.86)
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)
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 the total number of observations.

Table IA5: Summary of the Enforcement Directive (2004/48/EC)

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

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

Table IA6: Implementation dates of Enforcement Directive by EU 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
Latvia	03/2007	1.9
Lithuania	04/2006	2.1
Luxembourg	06/2009	3.5
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 actual implementation dates of the Directive 2004/48/EC across member states. The intended deadline for implementation was April 29$^{\text{th}}$, 2006. Respective dates are hand-collected from *Petillon (2019)*. Sample countries are highlighted in bold letters. The third column displays the fraction of patents that are designated to respective jurisdictions.

Table IA7: Covariates: pre- versus post-treatment comparison

Covariates		*Before*	*After*	Difference in means
(I) Firm size (log. assets)	Affected	10.199	10.831	0.632***
	Control	9.460	10.105	0.645***
(I) Profitability (RoA)	Affected	0.083	0.085	0.002
	Control	0.088	0.091	0.003
(I) Tangibility	Affected	0.221	0.204	-0.017***
	Control	0.230	0.218	-0.011***
(I) Cash flow	Affected	0.068	0.074	0.006**
	Control	0.071	0.074	0.004*
(II) Firm size (log. assets)	Affected	10.214	10.812	0.598***
	Control	9.464	10.122	0.658***
(II) Profitability (RoA)	Affected	0.081	0.083	0.002
	Control	0.089	0.092	0.003
(II) Tangibility	Affected	0.219	0.206	-0.013***
	Control	0.230	0.216	-0.014***
(II) Cash flow	Affected	0.068	0.073	0.005*
	Control	0.071	0.077	0.006**

Notes: The table presents mean values of affected and control firms' capital structure determinants 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 defined by Equation (1), i.e. number of active patents in all EPC jurisdictions. Second (II), we consider patenting expenses before the treatment as proxy for patent value by Equation (2). Capital structure determinants are defined in Table 4. Other specifications are equivalent to those in Table 6. The last column contains the differences in mean values, where *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table IA8: 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		2.319^{***}		5.345^{**}		0.191^{**}		0.019^{*}
		(0.877)		(2.380)		(0.079)		(0.010)
Patent value × Post	24.797^{***}		27.678^{***}		0.966^{**}		0.170^{***}	
	(7.857)		(10.207)		0.660)		(0.066)	
Patent value	-2.944	7.799	1.912	13.464	-0.092	0.355	-0.028	0.040
	(4.190)	(5.558)	(7.394)	(9.596)	(0.290)	(0.429)	(0.036)	(0.046)
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	0.08	0.08	0.02	0.02	0.16	0.16	0.09	0.09
Observations	24,023	24,023	28,868	28,868	21,925	21,925	25,735	25,735

Notes: The table presents estimates regressions repeating the baseline specification corresponding to Columns II and IV of Table 7. In the first two specifications (Columns I and II), we restrict the sample to observations with non-zero amount of loans using debt-ratio as defined in Table 4 as dependent variable. The remaining specifications use alternative definitions on the dependent variable: the non truncated values of the original debt-ratio measure (Columns III and IV), the logarithm of long-term debt (Columns V and VI) and the bank loan to total liability ratio (Column VII and VIII). All regressions include firm-level capital structure determinants, the level variable of the treatment variable, i.e. *Post* (in Columns II, IV, VI, and VIII), firm- and country-year-fixed effects. (Undisplayed) controls are defined in Table 4. 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 IA9: Baseline regression using alternative definitions of the main regressor

Dependent variable:	Debt-ratio					
Patent specification	Value (incl. age)		Stock size		Patent filings	
	(I)	(II)	(III)	(IV)	(V)	(VI)
Affected × Post		2.121**		1.378*		-0.121
		(0.751)		(0.820)		(1.041)
Patent value × Post	20.551***		7.642***		5.212**	
	(7.275)		(2.677)		2.527)	
Patent value	0.967	8.803*	-0.288	3.052	-1.036	0.765
	(4.094)	(0.091)	(2.363)	(2.650)	(0.957)	(0.946)
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	28,868	28,868	28,868	28,868	28,779	28,779

Notes: The table presents estimates regressions repeating the baseline specification corresponding to Columns II and IV of Table 7. Here, we vary the definition of the patent value measure: patent stock is measured by its number of active patents, jurisdictions, and age (Columns I and II), number of active patents (Columns III and IV), and the number of patents filings (Columns V and VI). Following Equation (4), all patent measures are included with their one period lag, regressions include firm-level capital structure determinants, the level variable of the treatment variable, i.e. *Post*, if appropriate (in Columns II, IV, VI, and VIII), and firm- and country-year-fixed effects. Variables are defined in Table 4. 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 IA10: Testing the crisis versus enforcement directive effect

Dependent variable:	Debt-ratio							
Patent value definition:	Patent stock				Patent costs			
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
Affected × Post			2.740***	2.475***			1.818***	3.512***
			(0.687)	(0.998)			(0.691)	(0.872)
Affected × Crisis			-0.128	0.073			-0.439	-1.471**
			(0.629)	(0.668)			(0.614)	(1.202)
Patent value × Post	13.433**	21.211***			1.346	4.317***		
	(6.473)	(6.880)			(1.308)	(1.523)		
Patent value × Crisis	6.407	3.201			0.794	-1.054		
	(5.816)	(5.365)			(1.141)	(1.170)		
Patent value	0.697	-2.240	7.431	7.324	-0.194	-0.927	0.383	0.072
	(3.720)	(3.764)	(5.023)	(5.065)	(1.039)	(1.080)	(1.095)	(1.094)
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	0.08	0.08	0.07	0.07	0.07	0.07	0.07	0.07
Observations	28,868	28,868	28,868	28,868	28,868	28,868	28,868	28,868

Notes: The table presents regressions repeating the baseline specification similar to Equation (4). In addition to the DID estimator introduced in the previous analyses, every regression includes a term interacting a dummy variable equal to one if the respective firms' home country is in a recession as defined in accordance with Laeven and Valencia (2013) with either the continuous patent value measure (Columns I-II and V-VI) or the ex ante treatment indicators (Columns III-IV and VII-VIII). For the treatment dummy (*Post*), we use both previous specifications: the binary indicator on whether the enforcement directive is implemented in the home country (Columns I, III, V, and VII) and the continuous variable measuring the fraction of the firms' designated states that implemented the directive (Columns II, IV, VI, and VIII). Further we use the two specifications for patent value, that is firms' patent stock (Columns I-IV) and patenting costs (Columns V-VIII). Following Equation (4), displayed variables are included using their first lag, regressions include firm-level capital structure determinants, the level variable of the treatment variables (i.e. *Post* and *Crisis*), and firm- and country-year-fixed effects. (Undisplayed) controls are defined in Table 4. 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 IA11: Assessment of anticipatory effects (pre-treatment)

Dependent variable:	Debt-ratio				
Treatment definition	Patent stock value	Patenting costs	Portfolio size	Portfolio value	Patent filings
	(I)	(II)	(III)	(IV)	(V)
$t-6$	1.371	0.223	-3.875	0.319	0.165
	(1.056)	(1.110)	(3.394)	(1.920)	(1.490)
$t-5$	0.556	-0.067	0.355	-0.463	0.913
	(0.829)	(0.866)	(2.605)	(1.285)	(1.013)
$t-4$	0.177	-0.321	-0.370	0.285	1.723*
	(0.802)	(0.840)	(2.959)	(1.220)	(1.037)
$t-3$	-0.380	-0.840	-2.285	-0.236	0.741
	(0.728)	(0.756)	(2.441)	(1.163)	(0.889)
$t-2$	0.626	0.282	2.614	0.640	1.010
	(0.654)	(0.690)	(2.257)	(0.999)	(0.841)
$t-1$	-0.129	-0.307	1.720	-0.408	0.390
	(0.520)	(0.554)	(1.907)	(0.778)	(0.696)
Additional controls:					
Firm-level determinants	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Country-Year FE	Yes	Yes	Yes	Yes	Yes
R^2	0.07	0.07	0.07	0.07	0.07
Observations	17,075	17,075	17,075	17,075	17,075

Notes: The table presents estimates from regressions explaining firms' debt ratios. The regressions contain 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 (Column I) or patenting costs (Column II) as specified in Equations (1) or (2), respectively. Further, we define treatment by the median ex ante patent stock size (Column III) and patent value (Column IV) as measured by the patent portfolio family size, i.e. number active jurisdictions, as well as by a dummy equal to one (zero) if the firm filed any (no) patents prior to the treatment. The sample is truncated by excluding firm-year observations in all years succeeding the implementation year of the Enforcement Directive. Hence, the reference time frame is the period t=0, i.e. the firm-specific year in which the treatment occurs. 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 IA12: Testing for pre-treatment trends

Dependent variables:	Debt-ratio				
	(I)	(II)	(III)	(IV)	(V)
Time trend (T)	-0.447***	-0.398***	-0.412***	-0.397***	-0.410***
	(0.097)	(0.119)	(0.117)	(0.110)	(0.107)
$T\times$ Affected (patent stock value)		-0.158			
		(0.182)			
$T\times$ Affected (patent costs)			-0.135		
			(0.181)		
$T\times$ Affected (stock size)				-0.244	
				(0.194)	
$T\times$ Affected (patent filing)					-0.239
					(0.235)
Additional controls:					
Firm-level determinants	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
R^2	0.04	0.04	0.04	0.04	0.04
Observations	14,270	14,270	14,270	14,270	14,270

Notes: The table presents estimates from regressions on firms' debt ratios testing for parallel trends between treatment and control group firms. Regressions include a time trend variable which is a running number for each year during that period. In Columns II-V this measure is interacted with an indicator variable equal to one if the firm has an above median patent stock value (Column II), patenting costs (Column III), patent stock size (Column IV), or whether the firm filed any patents (Column V) respectively, in the firm-specific year prior to the treatment. All variables are specified as above, including the applied control variables, i.e. firm-level capital structure determinants, in Table 4. All regressions further control for firm-fixed effects and capital structure determinants as defined in Table 4. In accordance to Angrist and Pischke (2008) the sample contains only observations from the pre-treatment periods. 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 IA13: Lag structure of the regression estimates (post-treatment)

Dependent variable:	Debt-ratio				
Treatment definition	Patent stock value	Patenting costs	Portfolio size	Portfolio value	Patent filings
	(I)	(II)	(III)	(IV)	(V)
t	0.403	0.777	0.581	0.655	-0.413
	(0.538)	(0.552)	(1.961)	(0.851)	(0.738)
$t+1$	0.368	1.318**	2.098	-0.052	-0.998
	(0.613)	(0.634)	(2.111)	(0.941)	(0.786)
$t+2$	1.176*	1.957***	2.687	1.245	-0.554
	(0.665)	(0.648)	(2.216)	(1.034)	(0.934)
$t+3$	1.719**	1.922**	5.205**	1.659	0.135
	(0.771)	(0.768)	(2.220)	(1.211)	(1.036)
$t+4$	3.394***	2.576***	6.889**	3.521**	0.045
	(0.928)	(0.905)	(2.813)	(1.409)	(1.190)
$t+5$	2.787***	2.199**	3.018	2.679*	-1.306
	(0.936)	(0.926)	(2.921)	(1.443)	(1.227)
$t+6$	3.424***	2.861***	8.359**	2.671*	0.369
	(0.952)	(0.970)	(3.730)	(1.391)	(1.233)
Additional controls:					
Firm-level determinants	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Country-Year FE	Yes	Yes	Yes	Yes	Yes
R^2	0.07	0.07	0.07	0.07	0.07
Observations	28,011	28,011	28,011	28,011	28,011

Notes: The table presents estimates from regressions explaining firms' debt ratios. The regression 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 (0-6) after the implementation of the Enforcement Directive, denoted as $t + j$ ($\forall j \in [0, 6]$). The treatment variable is defined equivalent to the Table IA11 (Internet Appendix). The reference time frame is the entire pre-treatment period but we keep a symmetric time window and exclude any observations six years before or after t=0. 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 IA14: 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, leather and related products, wood textile, wearing apparel, leather and related products, wood and of products of wood, paper and paper products, printing and reproduction of recorded media
	31	Manufacture of furniture
	32	Other manufacturing

Notes: The table displays our criteria for firms classifying as tech-oriented firm. We follow the sectoral classification 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 aggregated on the 2-digit level.

Table IA15: Firm-level heterogeneity: private versus publicly listed firms

Dependent variable:	Debt-ratio							
Firm-type:	Private				Publicly listed			
Patent value definition:	Patent stock value		Patenting costs		Patent stock value		Patenting costs	
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
Affected × Post		2.489***		2.643***		1.054		1.499
		(0.848)		(0.854)		(1.638)		(1.635)
Patent value × Post	26.872***		3.929***		-4.118		1.804	
	(7.560)		(1.604)		(6.151)		(2.635)	
Patent value	-2.555	8.892	-0.729	0.336	-4.742	-5.537	-2.567	-1.987
	(4.140)	(5.576)	(1.229)	(1.181)	(6.014)	(5.035)	(2.049)	(1.931)
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	0.07	0.07	0.07	0.07	0.13	0.13	0.13	0.13
Observations	26,708	26,708	26,708	26,708	2,160	2,160	2,160	2,160

Notes: The table presents estimates from regressions explaining firms' debt ratios. All variables and model specifications are defined as above, only we repeat the baseline regression for subsamples of firm that are privately owned (Columns I-IV) or listed on the stock market (Columns V-VIII). 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.

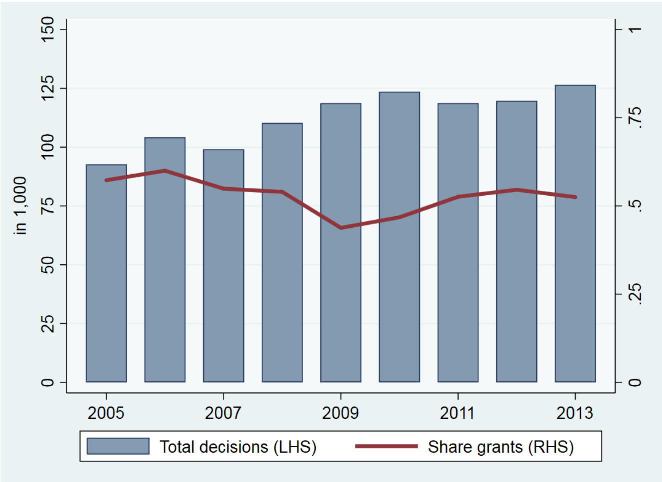
Table IA16: Application of injunction in different EU member states (as of 2003)

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 provides an example on the fragmentation of IPR enforcement in the European Union before the Enforcement Directive was implemented. The subject is the application of injunctions across different member states. The reference year of these rules is 2003. 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 of respective member states.

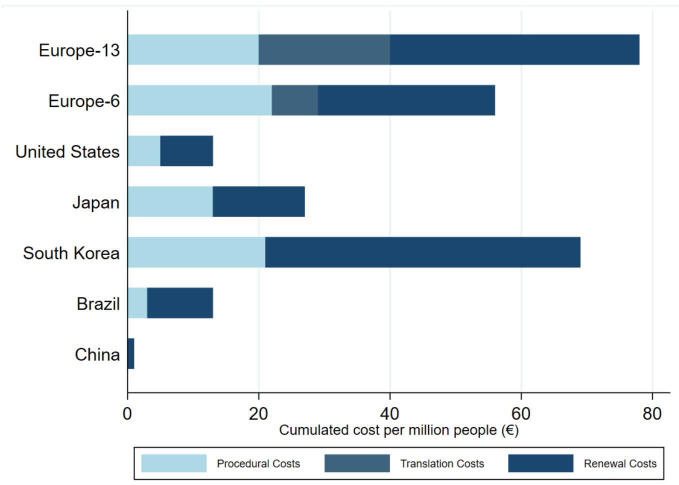
Internet Appendix B: Figures (IA1 - IA11)

Figure IA1: Patent decisions and grant rates at EPO (2005-2013)



Notes: This figure displays the total number of patent decisions on patent filings (blue bars, indexed on the left-hand side). Applications withdrawn prior to publication date at 18 months after filings are excluded. Further, the reg line plots granted patents as a fraction of total decisions (indexed on the right-hand side). Here, applications may not be granted due to refusal by EPO as well as deliberate withdrawal prior or during examination. Own illustration based on data from Harhoff (2016).

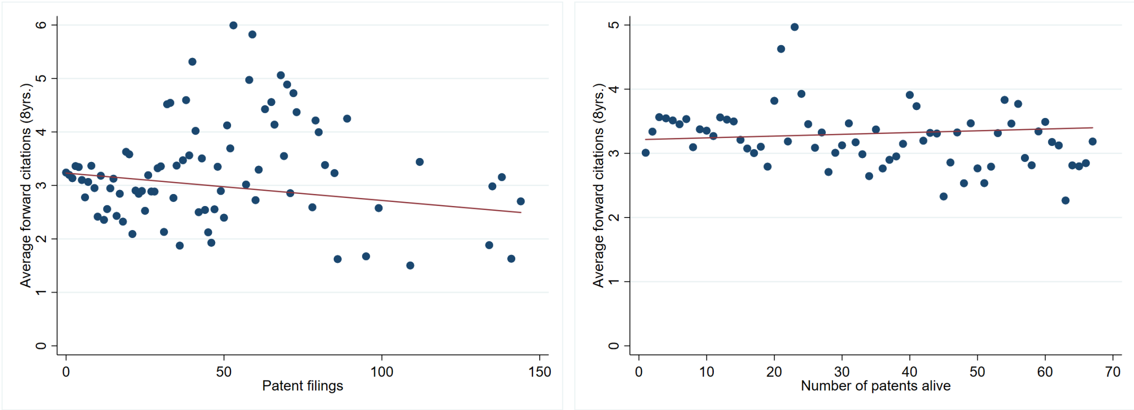
Figure IA2: Patenting costs: an international comparison of fees



Notes: This graph plots the cumulated costs per million people for six major 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 de la Potterie (2010).

Figure IA3: Relating patent citations to quantitative patenting measures

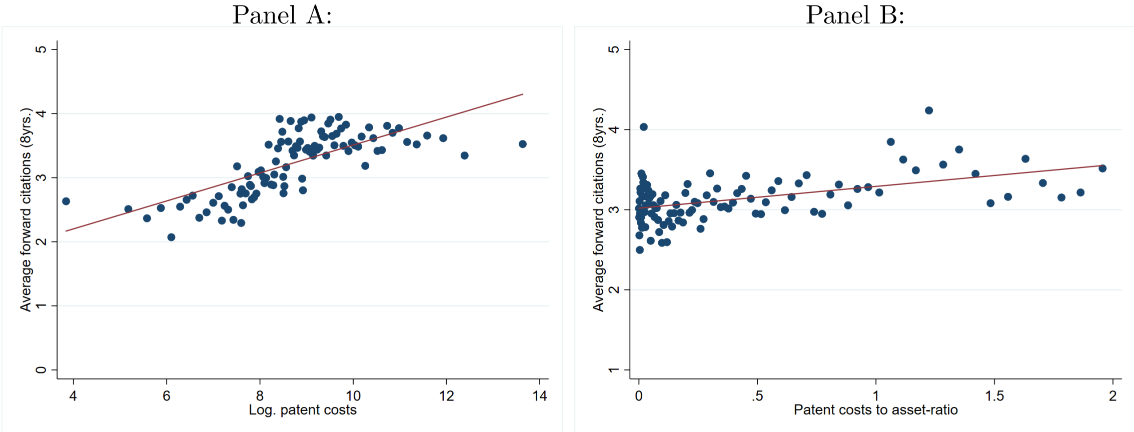
Panel A: Panel B:



Notes: This scatter plot relates the...

Figure IA4: Relating patent citations to alternative patenting costs measures

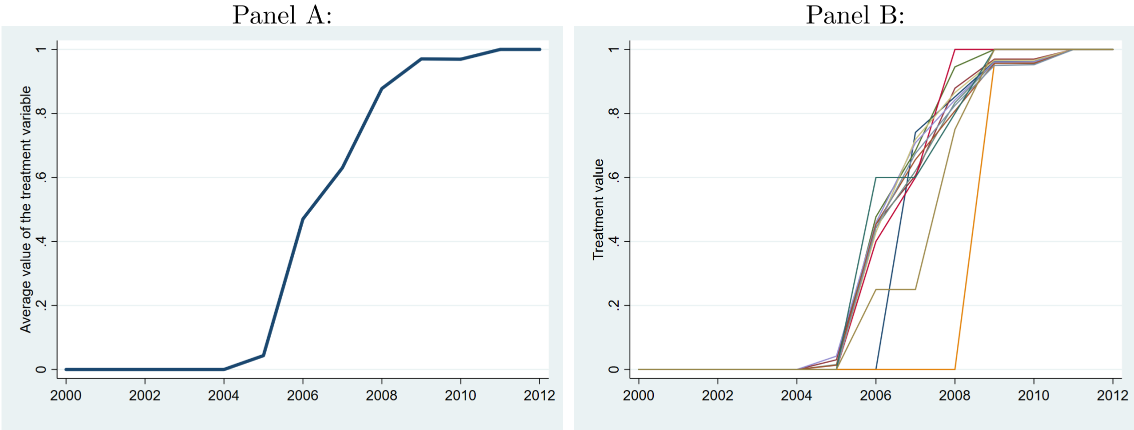
Panel A: Panel B:



Notes: This scatter plot relates the...

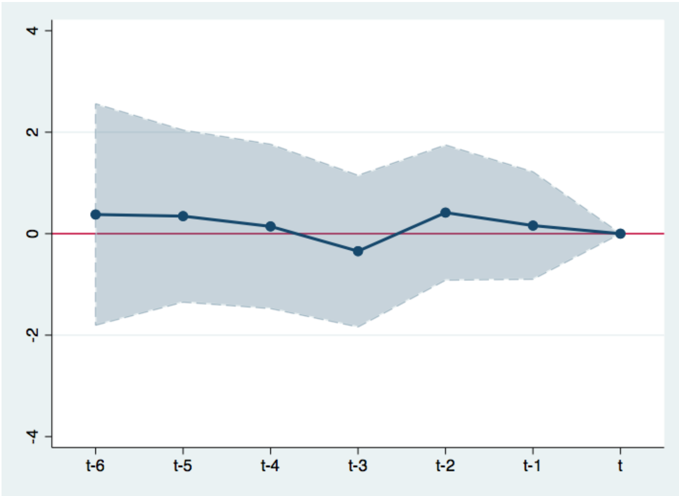
Figure IA5: Development of the treatment over time

Panel A: Panel B:



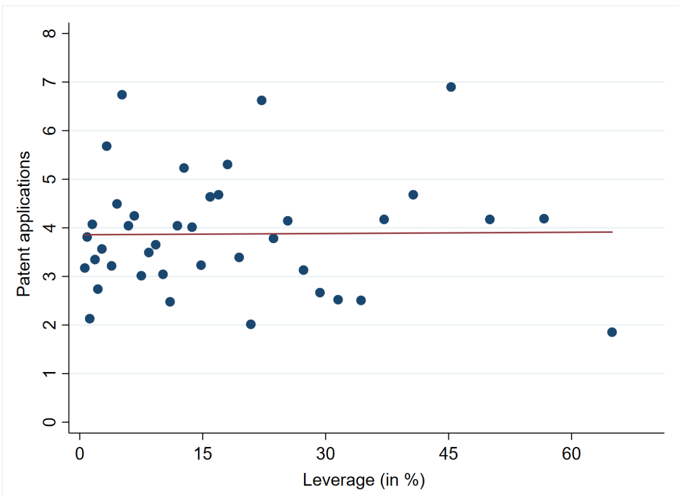
Notes: This figures plot the value of the treatment variable across the sample time span. Treatment refers to the relative share of all relevant jurisdictions of a sample firm which implemented the Enforcement Directive. For any firm, jurisdictions are relevant if at least one patent out of their portfolio is maintained in that respective jurisdiction. Hence, a value of 1 (0) resembles that all (none of the) jurisdictions have implemented the directive. For simplicity, we only consider the 37 EPC countries as relevant jurisdictions. Panel A displays the overall average value of this treatment variable. Panel B displays firm-specific values of twelve randomly selected sample firms.

Figure IA6: Deviation in pre-treatment trends (cost definition of affected firms)



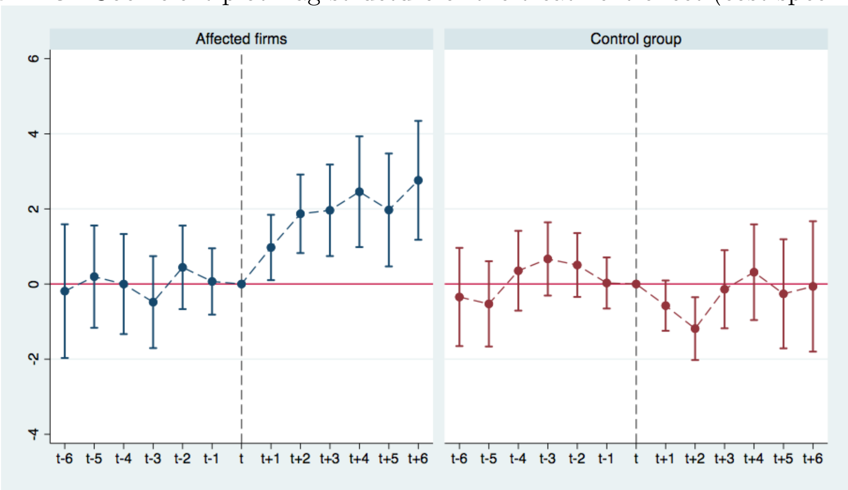
Notes: This figure plots correlation coefficients analogue to Figure 6 but uses a treated dummy indicating whether the firm is considered as a high patenting firm defined by median split according to the pre-treatment patent costs measure specified by Equation (2). All other specifications remain the same. The shaded area represents the 95 percent confidence intervals. The implementation year, t, is the base year.

Figure IA7: Binned scatterplot: Patent filings and leverage



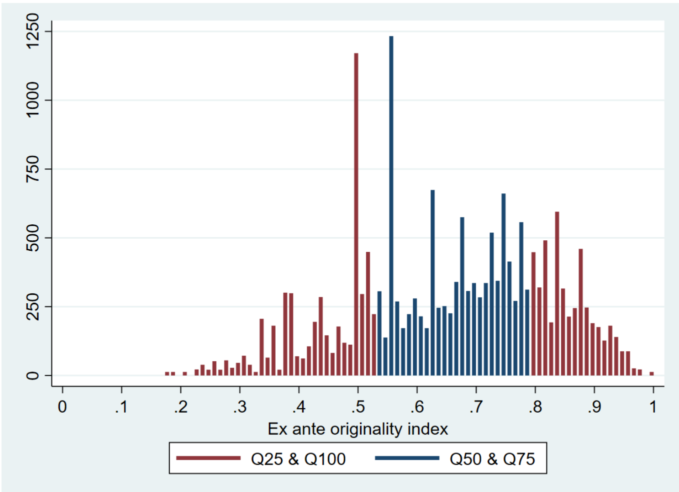
Notes: This binned scatterplot relates the number of patent filings (y-axis) to leverage ratios (x-axis) for our sample firms and displays the linear fit. The number of bins is set to 40.

Figure IA8: Coefficient plot: lag structure of the treatment effect (cost specification)



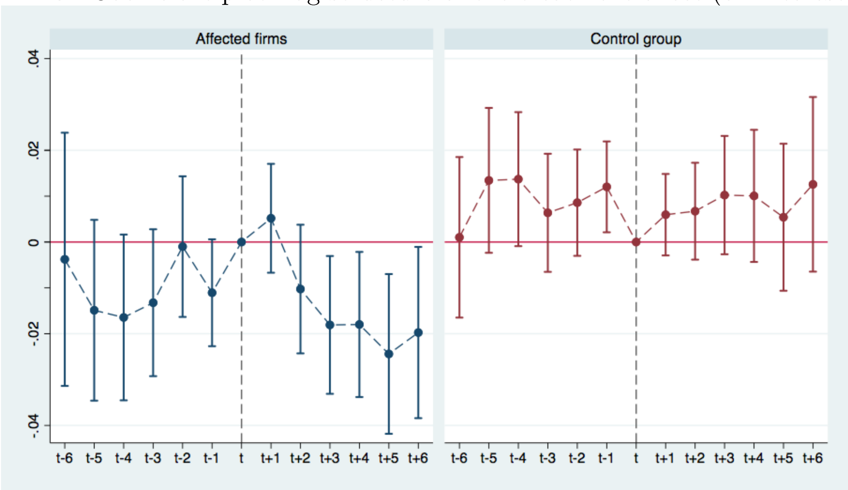
Notes: This figure depicts the development of treatment and control groups of patent portfolios on firms' leverage before and after the treatment analogue to Figure 7. Only here the treated dummy indicating whether the firm is considered as an ex ante high patenting firm is defined by median split according to the pre-treatment patent costs measure as specified by Equation (2). All other specifications remain the same.

Figure IA9: Pre-treatment originality index distribution



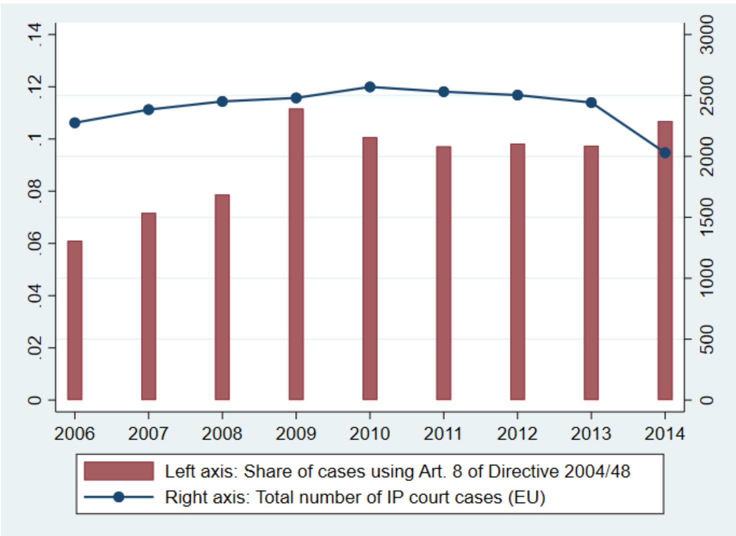
Notes: This histogram displays the distribution of the pre-treatment originality Herfindahl-index of firms' patent portfolios in terms of the absolute frequency of observations (y-axis). Originality is measured based on the number of different technology classes respective patents refer to: $originality_{it} = \sum_j^{n_i} bwd_{ij}^2$, 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 IA10: Coefficient plot: lag structure of the treatment effect (on interest burden)



Notes: This figure depicts the development of treatment and control groups of patent portfolios on firms' leverage before and after the treatment analogue to Figure 7. Only here the dependent variable is the interest burden ratio as defined in section 4.4 and regressions control for industry-year effects. All other specifications remain the same.

Figure IA11: 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 that take advantage of Article 8, the right of information, of the Enforcement Directive (2004/48/EC). The red bars resemble the shares (indexed on the left y-axis), while the blue line indicates the total number of IP court cases in the EU (indexed on the right y-axis). The time frame spans from 2006, the year in which the majority (>50%) of EU member states have implemented the Enforcement Directive until 2014, the most recent for which data is available. Own calculations based on data from European Union (2017).

Appendix C: How patenting supports external debt financing

I. Theoretical considerations and propositions

There are two ways in which firms may use their patent portfolio to support external debt financing: directly (asset-based lending) and indirectly (cash flow-based lending). For example, Mann (2018) shows that firms directly pledge patents as collateral allowing them to increase their debt capacity. Here, the pledge of the patent(s) is explicitly stated in respective loan contracts. Similar to asset-based lending with tangible property, debt is thus secured by specific assets, whose liquidation value is the key determinant of creditors' payoffs in bankruptcy. Importantly, Lian and Ma (2019) find that asset-based-lending only constitutes about 20% of non-financial corporate debt, whereas 80% of corporate debt is actually based on cash flow-based lending. This suggests that the indirect use of patents in loan contracts is likely even more important. Here, debt is not necessarily tied to a specific physical asset but rather based on future cash-flows.[28]

Further, patents can signal investors future performance (e.g. Spence 2002) and thus might help to attract debt financing in an implicit manner. 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 (2019) show that information disclosure as a means of signaling helps patenting firms to lower their costs of debt. Important for our analysis, meaningful signals comprise not only the application but also the maintenance of patents. For example, in Europe each firm has to decide whether or not to perpetuate a patent. Because of the repeated decision of incurring the costs of annual renewals, only valuable patent maintained (de Rassenfosse and Jaffe 2018).

Following these considerations, patenting should explicitly and implicitly support 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 tangible assets. Specifying the relevant dimensions of patenting in the context of firms' borrowing activities is necessary to appropriately test this presumption. While most analyses use patent filings as an indicator for firms' patenting activities, a sizable fraction of newly filed patents is actually very short-lived. In the European Union during the 2000s, the average share of granted patent filings is around 50% (see Figure IA1 in the Internet 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

[28] 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 margins and expansion of sales. Third, due to its purpose of granting temporary monopoly rights to the patent holder, patents fend off competitors by constituting entry barriers. Fourth, patenting allows for licensing, which directly generates streams of royalty payments. At the same time, of course, every patent that 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.* (2020) estimate causally that patent grants increase firms' sales growth on average by about 80% relative to non-patenting control firms.

necessary but not sufficient condition to effectively alter firms' debt capacity. Instead, only if a patent is still actively held, it should be a meaningful determinant for firm leverage. Hence, we suggest 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, the potential of attracting external debt significantly varies depending on the properties of the patent portfolio itself. Not all patents have the potential to increase firms' debt capacity, i.e. patents at the lower end of the value distribution are less likely to meet demand in the market as compared to those in the right tail. 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. Thus, we propose that only the combination of an economically meaningful amount *and* value of patents leads to higher debt to asset ratios of firms.

II. 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 (Mes 2015). 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.

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.

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.

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 rules for calculating damages or applying provisional measures and sanctions. Table IA16 (Internet Appendix A) exemplifies the fragmentation of IPR enforcement comparing 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 right holders 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 IA11 (Internet 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% of all IP court cases in the EU to almost 12% between 2006 and 2009.

In a more general perspective, 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% 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.