Leveraging the (Un)Known:

The Value of Patent Portfolios

By Andrej Gill* and David Heller†

We provide new evidence on the relevance of patents for attracting external debt financing. For a representative, multi-country sample, we find large positive effects of valuable patent portfolios on firms' debt capacity. To study this, we develop a novel patent portfolio value measure using granular information on patent fee payments. For identification, we investigate exogenous variation in patent strength arising from the staggered implementation of the 2004 EU Enforcement Directive. Results are strongest for financially constrained firms, which emphasizes the strategic potential of patents. Moreover, our findings highlight the importance of a harmonized, reliable legal framework to spur these effects.

JEL Classification: G30; G32; O32; O34
Keywords: Intellectual property, debt financing, patent valuation, borrowing constraints

1 Introduction

Intangible assets, such as intellectual property (IP) rights, constitute the majority of firm value in industrialized countries (Haskel and Westlake 2018). Deploying the value of these rights for purposes other than protecting inventive activities appears promising, in particular, for innovation-intensive firms. These firms are typically characterized by an inherent opacity and high valuation risk which increase agency costs and impede external financing activities (e.g., Hall and Lerner 2010). 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. Empirical evidence indicates that patents, as one prominent example of an IP right, are a potential solution to this by improving access to external financing (Farre-Mensa *et al.* 2020). Specific types of borrowers are even found to directly use patents in loan contracts as collateral (Mann 2018, Hochberg *et al.* 2018). Hence, understanding the underlying mechanisms that enhance innovation-intensive firms' debt capacity is of highest importance to spur external financing and thus firm development.

*Department of Economics and Business Administration, Johannes Gutenberg University Mainz; Jakob-Welder-Weg 9, 55128 Mainz, Germany; Phone: +49 (0)175 5919293; E-Mail: gill@uni-mainz.de
†Max Planck Institute for Innovation and Competition; Marstallplatz 1, 80539 Munich, Germany; Phone: +49 (0)89 24246 565; E-Mail: david.heller@ip.mpg.de

In this study, we provide new evidence by investigating the effects of patenting activities on debt financing. Thus, we are first to disclose encompassing evidence that explores the relevance of patents as a determinant for firms' debt capacities, moving beyond specialized borrowers, potential conditions that support this relationship, and their actual implications for innovation-intensive firms. For this, we analyze characteristics on the firm-, patent-, and country-level using a unique sample which comprises firms from virtually all life cycle stages, sizes, and legal forms. Two novel features further augment our analysis by revealing several decisive factors that affect the link between firms' patenting activities and their use of debt. First, we develop a new way to measure the size and the value of firms' patent portfolios. This accounts for the fact that our empirical setting requires a widely applicable patent measure, which can be compared across a variety of firms. As a second new dimension, we study a major legislative change in Europe, the Enforcement Directive, as a source of exogenous variation in the strength of patent enforcement. Stronger and more harmonized patent protection enhances expected patent value, since it determines the appropriability to patent investments. Heterogeneity in the timing and the intensity of the change in law allows us to exploit this event as a natural experimental setting. Combined with our patenting measures, we can therefore establish a causal link between firms' patenting activities and their debt capacity.

Our baseline estimations show that firms with more valuable patent portfolios prior to the implementation of the Enforcement Directive increase their debt ratios on average by an additional 17% after the implementation compared to firms without valuable portfolios. This sizable effect is surprising, since it is estimated for the average patenting firm. Moreover, we find that portfolio size and portfolio value are complements for firms' ability to attract debt, whereas more simple patenting indicators, such as patent filings, are not able to explain our results. Heterogeneous treatment effects reveal that specific characteristics of the patenting firm and its patent portfolio determine the strength of the main effects. We find the largest effects for firms in countries which strengthened patent enforcement the most and for firms in more competitive environments. As firm-specific determinants, results are pronounced for medium-sized firms, particularly if they hold complementary tangible assets. To examine the implications of our findings, the final part of the analysis investigates whether utilizing patent portfolios helps innovative firms to alleviate financing constraints. Indeed, we show that the positive effect on debt ratios is largest for previously constrained firms and that these firms benefit from lower costs of obtaining debt. Overall, our findings therefore highlight the broad potential of

patents as strategic devices to support debt financing and demonstrate the importance of a harmonized and reliable IP enforcement framework to trigger these effects.

To study this, we combine in-depth European patent data (PATSTAT) on almost 100,000 individual patents with firm-level balance sheet information (ORBIS). This data is complemented with detailed, hand-collected information on patent fee schedules and country-specific information on the Enforcement Directive for all relevant European countries. Our dataset covers ten different European countries, virtually all industries, and comprises a time span of 13 years, sampling the years 2000-2012. Further, our sample is fairly representing the true European business landscape by predominantly comprising small private firms.

Equipped with this data, we address several empirical challenges. Common metrics of patenting activities, such as patent filings or citations, are not suited to establish a link between the actual value of patent portfolios and firms' debt capacities. Foremost, this is because the overall value of firms' patenting activities should mainly depend on the portfolio size and portfolio value of actively maintained patents, which both vary over time.[1] Our analysis thus introduces a novel way to quantify firm-level patent portfolios by drawing on a combination of institutional features of the European patent system and highly disaggregated data. Our measurement approach builds on the idea that patenting expenditures are informative about the fundamental value of an invention (Schankerman and Pakes 1986). In this context, using the EU as the empirical setting is advantageous, because European patent fees have to be paid every year *and* for every single designated member state. We explore this variation and track payments for each individual patent to measure the size and value of firms' actively held patent portfolios on a yearly basis. Further, patenting expenses are applicable for any firm irrespective of its life cycle stage, size, or legal form. Hence, our approach takes virtually all patenting firms into account. One potential threat to this measurement strategy could be that patenting costs only inform about the lower bound of expected portfolio value. Importantly, we therefore show that our measures do not only reflect a minimum expected return to patent investment but also explain the upper part of the value distribution as they positively relate to common measures of patents' technological quality and value. Thus, our patent portfolio measures are able to capture the entire patent value distribution.

[1] For example, common measures related to the value of patents typically refer to the timing of patent filings, such as information revealed on specific dates (e.g., patent filing, the degree of novelty at application, or stock market reactions upon patent publication) or backward-looking quality measures (e.g., patent citations). However, technological progress evolves over time implying that a valuable invention today may not be as meaningful in the future. Hence, these measures are not fully informative about the actively held stock of patents. Notably, frequent ownership changes and patent lapses within years after filing exacerbate these issues.

Furthermore, studying the effect of patenting on external debt financing entails obvious endogeneity concerns. For example, it is a priori not clear, whether patenting enhances firms' debt capacity or whether firms obtain more debt to finance patenting activities. We follow a multi-layered approach to establish a causal link of patenting on firms' debt capacity, which explores plausibly exogenous variation in patent rights enforcement arising from the implementation of the European Commission's Enforcement Directive. This major legislative change became effective at different points in time across EU member states and enhanced patent protection during the mid-2000s by harmonizing and improving the enforcement of IP rights. The intuition behind this is that improvements in patent strength increases the expected returns to patenting (Bessen and Maskin 2009) and thus determines the ability of patents to secure debt (Rampini and Viswanathan 2013). In our baseline setting, we use a difference-in-differences (DID) design for a sample of patenting firms in which we explore additional variation in the exposure to the treatment by distinguishing among firms' ex-ante patent portfolio values. Results show that the strengthening of IP right enforcement leads to a causal increase in debt ratios for firms that possess a more valuable patent portfolio prior to the change in law. Estimating this, we control for common capital structure determinants as well as country-year and firm fixed effects. Several supplementary analyses verify the applicability of our estimation approach, such as testing for parallel pre-trends between affected and control group firms.

Importantly, we extend our baseline approach in several ways. First, to control for confounding factors that arise from differences in observable firm characteristics, we construct a control group of non-patenting firms using Coarsened Exact Matching (CEM). This creates an alternative definition of comparable treatment and control groups to re-estimate the DID setting. Results from this approach are similar to the main findings both in significance and in magnitude. Second, we extensively test the intuition that a relatively broad legislative change should have heterogeneous effects depending on the ex ante market environment. To study this, we first quantify the country-specific extent to which IP enforcement was strengthened. We collect detailed information on the actual amendments to the previously existing law on a country-by-country basis to calculate a country-amendment matrix. Our estimations show that effects are stronger for firms domiciled in countries with a higher exposure to the treatment, i.e., with more amendments to the national legislation, and vice versa. Furthermore, to move away from country-specific factors, we investigate different industry-specific intensities in competition prior to the change in law. This approach builds on the idea of the escape

competition effect (e.g., Aghion *et al.* 2005), which states that incentives to engage in costly innovation increase with improved chances to capture higher returns from innovative activities. Confirming this assumption, we find that the propensity to respond to the Enforcement Directive increases with stronger ex ante competition. Next, we mitigate concerns that other, timely proximate events to the change in law are better able to explain the main findings. As such, we show that the effects are only observable once the Directive becomes effective and not upon its announcement, which is in line with prior research on changes in law enforcement (e.g., Papageorgiadis and Sofka 2020). Finally, in several placebo tests we find that other contemporaneous events, like the global Financial Crisis, are unlikely to be omitted factors that drive our main results.

To reveal further specific determinants for the relationship between patenting and debt financing, we test several observable firm-level characteristics. This is of particular interest with regard to the general applicability of the positive effect of valuable patent portfolios on firms' debt capacity. First, we asses firm size prior to the change in law, because patent portfolio size and firm size are positively related. However, we find that effects are strongest for small and medium-sized firms, whereas firm size itself is not sufficient to explain the main findings. Second, since tangible assets are a well-known capital structure determinant, we explore whether these assets serve as complements to patents for attracting debt. Results show that having relatively fewer tangible assets dampens the positive effect of valuable patent portfolios. Yet, having particularly many tangibles (i.e., being in the top quartile of tangibility) does not lead to larger effects. Hence, these analyses show that the positive effect of patenting indeed applies for the average firm, i.e., moving beyond the known cases of specialized borrowers.

As a concluding step, we show that a strengthened and harmonized patent enforcement law helps to relax financing constraints of firms with valuable patent portfolios. To study this, we test several definitions of financing constraints and find that ex ante constrained firms benefit most from the Enforcement Directive. Respective firms disproportionally increase their debt capacity, while facing lower costs of obtaining debt.

Our study relates to different branches of literature. Most generally, we contribute to the literature on financial constraints of innovative firms. A large body of research finds that innovation-oriented firms face difficulties to obtain debt financing, because of the uncertain and volatile returns as well as the limited collateral value associated with innovative projects (e.g., Berger and Udell 1998, Hall and Lerner 2010). Compared to the rich literature testing for the presence of financing constraints for innovation-oriented firms, we focus on inventive outcomes as a means to mitigate constraints. Hence, our

paper directly adds to the literature on the use of intellectual property for obtaining external debt financing. While the use of easy to liquidate tangible assets is conventionally considered the prime mode for securing debt (e.g., Graham and Leary 2011), the use of intangibles appears more important than conventionally expected. 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 IP rights enhance access to both equity as well as debt finance by reducing information asymmetries via signaling (Haeussler *et al.* 2014, Saidi and Žaldokas 2021), lowering spreads on bank loans (Chava *et al.* 2017) or being pledged as collateral to raise debt financing (Mann 2018, Hochberg *et al.* 2018). More generally, Farre-Mensa *et al.* (2020) argue that obtaining a patent causally facilitates firms' access to external funding sources. We extend this strand of the literature by providing new insights on the relationship of patenting activities and firms' debt capacity.

In addition to this, a large strand of the literature investigates the effect of firms' legal environment and innovative activities, mostly focusing on the effect of changes in (IP-related) law (Aghion *et al.* 2015) or economic and financial development (Kerr and Nanda 2009, Chava *et al.* 2013) on inventive output. Others have studied the role of IP rights on cross-border technology transfer and diffusion (Cockburn *et al.* 2016). In contrast, this study analyzes the effect of a major legal amendment on firms' ability to monetize their intellectual property. Against the background of the strongly fragmented global patent system (see Hall and Helmers 2019), analyzing the effects of a more harmonized system in a multi-country setting is particularly important.

Finally, we add to the growing body of research that develops value-related measures of intellectual property. Our analysis introduces an entirely new approach to quantify patenting activities by precisely tracking fee payments of actively held patents. This enables us to quantify comparable information on virtually all patenting firms irrespective of their life cycle stage, size, or legal status and is different to previous approaches, which are best suited for specific subsets of firms. For example, Kogan *et al.* (2017) use stock market reactions after patent publication to assign dollar values to patents. Their measurement strategy is intriguing when studying public corporations, but it cannot directly be applied to private firms. Giuri *et al.* (2007) assign prices for patents by self-reported estimates of their inventors. Despite concerns about self-reporting biases, this approach is hardly scalable to a large sample such as ours.

Closest to our paper is the work by Mann (2018) and Hochberg *et al.* (2018), who provide important insights on the relationship of patenting and bank lending by inves-

tigating patents that are explicitly pledged as collateral in loan contracts. Yet, relying on explicit pledges in the US is problematic, since there are no consistent registration requirements across states (e.g., Jacobs 2011).[2] Moreover, Mann (2018) considers large, public corporations that commonly have a larger stock of tangible assets and a longer track record, which helps them to secure external financing. Hochberg *et al.* (2018) investigate a set of start-ups from three distinct technology subsectors that already receive VC financing and use patent-backed debt to prolong their VC-investment cycle. We deliberately choose a different approach, as we do not focus on such particular settings in which firms already have established funding channels or a long track record. Instead, we analyze firms from virtually all life cycle stages, industries, and legal forms, moving beyond the cases of specialized borrowers. This enables us to disclose new and more broadly applicable insights on the effect of patenting activities on firms' debt capacity. In addition, our novel empirical strategy deepens these insights even further by studying new dimensions of patent portfolio values in the context of a major legislative change that enhanced patent right enforcement.

The remainder of the paper is organized as follows. Section 2 introduces our patent measurement strategy, including the institutional background and descriptive analyses. In Section 3, we describe the data and our empirical approach, namely the Enforcement Directive. In Sections 4 and 5, we present our empirical results, robustness tests, and an analysis on heterogeneous treatment effects. Section 6 concludes.

2 Measuring firm-level patent portfolios

2.1 The institutional framework: patent fee schedules

Patent holders have to pay administrative fees to activate and sustain the protection of their invention. However, patent systems and especially their renewal schemes notably differ between jurisdictions. In Europe, usually beginning with the third year after initial filing, patent holders are obliged to pay renewal fees to perpetuate protection. In case of non-payment, the patent right lapses after a six-month grace period. Renewal fees have to be paid for every year *and* in accordance to the geographical scope of the patent, i.e., in how many member countries of the European Patent Convention (EPC)[3] patents

[2] According to Jacobs (2011), it is not mandatory to report security interests at the United States Patent and Trademark Office (USPTO). Similarly, Graham *et al.* (2018) document that conflicts in federal- and state-law as well as specific court rulings render the completeness of security interests recorded by the USPTO as uncertain. In the absence of consistent documentation, it is likely that this data suffers from selection issues, particularly in the case of small and medium-sized firms.

[3] 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 Mace-

are maintained. Thus, patent protection can be obtained and sustained independently across national European patent offices, implying that patent holders have to choose every year and on a country-by-country basis where to maintain protection. This feature differs from regulations in other main jurisdictions, such as the US, where payments are collected only three times over the course of 20 years. Similarly, a patent granted from the US patent office (USPTO) provides protection in all US states simultaneously.

A crucial property of the required fees is that they vary across patent life and designated countries: Renewal fees are relatively low during the first years after patent filing, but increase exponentially over time, making the last years of a patent's life the most expensive ones. While this structure of rising fees applies for all EPC jurisdictions, the exact amount varies substantially across member countries and patent age. Importantly, in an international comparison, patenting costs in Europe are relatively high. For example, depending on the geographical scope, maintaining a patent in Europe is between five to twenty times more expensive as compared to the US (de la Potterie 2010).[4]

Figure 1 illustrates how these components affect total patenting costs. Since each additional jurisdiction in which a patent is active increases the amount of renewal fees, patenting costs vary substantially with the number of designated countries (Panel A). Further, for a patent held in multiple jurisdictions over its maximum protection period, renewal costs constitute the largest share among all patenting expenses (Panel B).

- Insert Figure 1 here -

2.2 Measurement strategy

For our measurement strategy, these features are essential. As such, the annual renewal decisions directly indicate the validity of a patent and therefore closely record the active use of patents over time (EPO 2018). Renewal payments thus help us to determine the active use, geographical coverage, and age of individual patents at every point in time. This is crucial because most common patent variables that indicate ownership (e.g., patent filings or grants) only specify the patent owners at one distinct point in time but not over time. Statistics in Figure 2 illustrate that this has important implications for measuring the active use of patents. For example, Panel A shows that in many cases patent applications may never become effective. The share of non-granted applications at EPO between 2005-2013 is around 50%. Moreover, Panel B displays that even if

donia, Norway, Poland, Portugal, Romania, San Marino, Serbia, Slovakia, Slovenia, Spain, Sweden, Switzerland, Turkey, and the United Kingdom.

[4] Figure IA1 (Internet Appendix B) compares patenting costs across the main jurisdictions worldwide.

patents are granted, the majority of them lapses soon after filing. Indeed, one out of two patents filed at EPO lapses within the first seven years after application.

- Insert Figure 2 here -

We exploit these institutional features to develop a set of new, broadly applicable patent measures that capture firm-level portfolio values on an annual basis. Specifically, the annual renewal payments help us to identify patent-level maintenance for each patent owner and at any given point in time after filing. Based on this, we can consistently track firm's actively held patents over time. As an essential addition, renewal payments inform about the exact geographical scope of each patent. For any given year, we can thus determine each individual country where a patent is actively maintained. We combine the annual count and geographical coverage of patents to calculate our first patenting measure, which we refer to as the size of a firm's actively held *patent stock*.

We augment this measure by exploiting variation arising from country-specific differences in patent fee schedules. We therefore hand-collect information on the obligatory fees from various legal documents. Table IA1 (Internet Appendix A) summarizes them in a patent-year, country matrix. Based on information about active jurisdictions and the age of each patent within a portfolio, we calculate annual firm-level patenting expenditures. 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.[5] To calculate total patenting expenses, we thus include common fees that arise during the first years after submission of the patent application. We add up all costs items for each firm-year observation and refer to this measure as a firm's *patent costs*.[6]

To ensure that results are not driven by the distinct variable definitions, we include different variants of the measures in robustness tests. We normalize all patenting variables on an industry-year basis to mitigate concerns regarding strategic patenting behavior, which is correlated with industry- and time-specific characteristics of firms (Lerner and Seru 2021).[7] Summarized, we define the two main patent measures as:

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

$$patent\ costs_{it} = \sum_{1}^{P} fees_{it} \quad , \tag{2}$$

[5] Application costs include fees for the examination, international search, translation, and filing of patents. In the case of patent grant, firms additionally have to pay designation and grant fees. We sum up all application- and grant-related costs and assign them evenly to the first three years of patent life.

[6] Table IA2 (Internet Appendix A) displays the cost components involved over a patent life cycle.

[7] Normalized values, $\tilde{p}$, of any patent variable, p, for firm i in period t are calculated by: $\tilde{p}_{it} = p_{it}/Q99\,p_{st}$. Accounting for outliers, $Q99\,p_{st}$ is the 99th percentile value of variable p in sector s at time t and replaces all $p_{it} > Q99\,p_{st}$. The main findings are robust to using non-normalized variables.

where $jurisdictions_{it}$ is the average number of jurisdictions of all active patents, $act.\ patents_{it}$, of firm i at time t. 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 legal fees paid to file and maintain patents $1...p$ in year t.

2.3 Patent portfolio costs and the value of patents

Next, we test the central assumption behind our measurement strategy, which is that patenting costs are informative about the underlying value of the entire patent portfolio. In general, we expect particularly valuable patents to have a larger international scope and longer life span compared with portfolios of relatively lower value. This is consistent with previous literature, which identifies a strong positive relationship between individual patent value and both patents' geographical coverage (Harhoff *et al.* 2003) and maintenance (Schankerman and Pakes 1986). Since the geographical scope and patent age are main cost drivers of patents, valuable patents should be more costly to maintain relative to low value patents.

We first examine this assumption by considering the properties of the patenting measures. Table 1 displays summary statistics on common indicators of patent quality and the cost-related patenting measures for our sample.[8] The median cost per patent is 1,400 Euros and the median portfolio cost is 26,600 Euros. With an average patent life in our sample of eleven years, this resembles a net value of about 300,000 Euros. These rather low values are consistent with the fact that a median patent is not very influential for subsequent innovation. For example, Column II of Table 1 shows that the median patent only receives two citations, while a significant share receives no citations at all. Yet, relatively important patent portfolios are also significantly more expensive. Patent portfolios in the top five (one) percentile accrue costs of approximately 8.3 million Euros (49.4 million Euros) over their lifespan. These values are in line with previous literature by showing that market values strongly vary across patents with the majority of patents having little value and only a few patents reaching significant economic values (e.g., Gambardella *et al.* 2007). Notably, while our cost-related measures feature much higher variation on the lower tail of the patent value distribution as compared to common patent quality measures, they have a similar shape on the upper tail.

- Insert Table 1 here -

[8] Benchmarking these statistics to related studies shows the consistency of our sample. For example, in our sample about 19% of patents receive no citation compared to 16% in Kogan *et al.* (2017).

To emphasize the explanatory potential of our measures in more detail, we show that patent costs identify high value patent portfolios. This is important, as it addresses concerns that patenting fees may be limited to reflect the lower bound of expected patent value. By definition, the institutional setting caps total patenting costs for one individual patent at approximately 200,000 Euros. To show that patenting costs are suited to detect high quality patents, we relate our measure to existing patent indicators that are associated with market value but do not have a maximum threshold.

We start by analyzing the relationship between our measure and citations received by patents in firms' portfolios. The number of citations received is one of the most common patent measures and is typically used to approximate the technological importance and economic value of a patented invention (e.g., de Rassenfosse and Jaffe 2018). In Figure 3, we relate the average number of citations received within eight years after filing to the average patent costs of a firm, which shows that higher costs are associated with more citations. Importantly, the linear fit suggests that higher patenting costs are associated with higher technological quality along the entire distribution of patenting costs. Figure IA2 (Internet Appendix B) shows that this observation is robust to using alternative patent cost measures, such as the logarithm of patent costs (Panel A) and the patent cost to asset ratio (Panel B), but does not apply for more simple patenting measures, such as the patent stock size or patent filings (Panels C and D, respectively).

- Insert Figure 3 here -

Moving one step further, we test whether our measures are even able to explain truly important inventions using patent generality as a proxy for breakthrough patents (see Hall *et al.* 2001). Patent generality measures the breadth of technology classes associated with received citations. Higher values indicate that patents are relevant for a larger number of inventions across a wider range of technology classes and thereby indicate particularly valuable technologies. Specifically, we estimate the top 25, 10, and 1 percentile of the generality values within each portfolio, since these (maximum) values are better able to explain the presence of truly novel patents as compared to portfolio level averages. Choosing these relatively broad categories also accounts for the fact that firms may have only relatively small patent portfolios. We estimate the relationship between these generality values and the patenting costs of a firm i by:

$$generality_{it}^{q} = \gamma + \gamma_1 patent\ costs_{it} + \gamma_2 X_{ij} + u_{ij} \quad \forall\ q \in \{25, 10, 1\}. \tag{3}$$

The vector X controls for i) observable time-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 flow), ii) observable time-invariant firm characteristics by including firm fixed effects, iii) firm-year fixed effects that account for macroeconomic changes, and iv) country-industry fixed effects that account for industry-specific patenting behavior as well as institutional cost differences. Standard errors are heteroscedasticity-consistent and clustered at the firm level. Results in Table 2 show a strong positive association between patenting costs and high generality scores. Estimates are statistically significant at the one percent level and robust across different specifications. In line with our measurement strategy, the size of the point estimates increases for higher values of generality scores.

- Insert Table 2 here -

Combining these above insights strongly suggests that patenting cost-related measures are able to explain the underlying value of patented inventions. While the face value of patent costs can be interpreted as the lower bound of expected value, its magnitude explains variation in the entire quality spectrum of firms' inventions. Importantly, patent costs also explain the upper tail of the patent value distribution and are even able to identify truly novel inventions. These observations suggest that patenting costs proxy value proportionally by mirroring firms' willingness to pay. This reflects the idea that a patent renewal payment reveals information on both firms' expected returns for the next period as well as the option value to renew the patent in any future period.

3 Patent portfolios and debt: the empirical approach

3.1 Data and descriptive statistics

Our main sample is based on firm-level financial information from the ORBIS database provided by Bureau van Dijk covering the years 2000-2012 and ten European countries (Belgium, Denmark, Finland, France, Germany, Ireland, Italy, the Netherlands, Sweden, and the United Kingdom).[9] We exclude observations with zero or negative total assets, firms with missing industry class information, financial firms, and those active in public sectors and truncate all financial variables at the 1st and 99th percentile. Fur-

[9]Table IA3 (Internet Appendix A) displays the sample distribution across countries. From the original EU-15 member states in 2000, we have to exclude Austria, Greece, Luxembourg, Portugal, and Spain due to inconsistent data availability in ORBIS. For the remaining countries, the distribution of observations among countries represents the actual population shares, except for Italian firms, which have a low matching rate of patent and financial data.

ther, the main sample comprises firms with at least one active EPO patent throughout the sampled period. Patent-level information are aggregated on the firm-year level and obtained from the PATSTAT database, which contains the universe of patent applications for the relevant time span. In total, information on 96,800 individual patents are gathered and aggregated to 51,719 firm-year observations (representing 6,123 firms). 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.

Table 3 (Panel A) provides summary statistics on financial and patenting variables for our sample of patenting firms. In line with our research agenda, the majority of sample firms feature representative characteristics: They are privately held, fairly well established, and of medium size, with a median age of 18 years and a median employee count of 96, respectively. In total, only 5.3% of the sample firms are publicly listed. While the manufacturing sector is traditionally the most patent-intensive industry, the sample comprises virtually all industries with the few exceptions of those that we deliberately excluded for consistency reasons (see Table IA4 Internet Appendix A). Patenting activities vary strongly across firms. While the average firm holds about seven patents, the maximum portfolio size is 2,684 patents. On average, patents are renewed five times and validated in eleven jurisdictions. However, these patterns vary strongly: Some patents are never renewed or validated in only one jurisdiction, whereas others are renewed as often and in as many jurisdictions as possible.

- Insert Table 3 here -

3.2 The Enforcement Directive as identifying event

Our identification strategy uses the staggered implementation of the so-called Enforcement Directive (EU Directive 2004/48/EC) as a natural experiment improving patent enforcement across EU member states. The general objective of the Enforcement Directive is to harmonize legislative systems in EU member states to ensure a high and homogeneous level of protection of intellectual property rights. Specifically, it aims at *"creating an environment conducive to innovation and investment"* (Art. 1) and therefore sets out several measures, procedures, and remedies to ensure the enforcement of respective rights.

A comprehensive evaluation study of the EU (2017) ascertains that the Directive is an effective tool to harmonize the enforcement of IP rights across member states. Further, the new rules are found to significantly strengthen IP protection and to prevent IP right

infringements. In particular, Fleissner (2009) finds that the amendments enhance resilience against illegal copying and thereby strengthened the role of IP rights. Important for our analysis, the Enforcement Directive strengthened the reliability and effectiveness of patent rights through improving civil enforcement in a harmonized cross-country setting. Internet Appendix D provides further details on the effects of the Enforcement Directive and Table IA5 (Internet Appendix A) summarizes its main articles.

Our identifying assumption is that the adoption of the Directive enhances patent right enforcement and thereby increases the relevance of patent portfolios in the lending decision of potential loan providers. The rationale behind this is based on the fact that patent value strongly depends on the potential to extract value from the protected invention, which depends itself on the underlying right to exclude competitors. For instance, inventions are often not alienable in contracts and therefore subject to ownership conflicts and piracy. More thorough enforcement of patent rights impedes such an unlawful use of inventions. Following this, we expect enhanced enforcement to improve the appropriability of patent rights and, hence, to increase expected returns to patenting.

These considerations are backed by a large strand of literature. The legal environment has been identified as an important determinant for inventors to appropriate returns on their intellectual property (e.g., Aghion *et al.* 2015). Similarly, Bessen and Maskin (2009) show that a certain degree of enforcement leads to valuable follow-on inventions and ultimately to higher future profits, especially in environments with sequential innovations. Important for our purpose, Rampini and Viswanathan (2013) directly show that limited enforcement determines collateral constraints, while Gambardella *et al.* (2007) find that free riding on other firms' inventions becomes more difficult, once patent protection is enhanced. These aspects have real implications, for example, more effective patent protection enhances the propensity to license patents in the absence of complementary assets (Arora and Ceccagnoli 2006). Consistent with this, exogenous variation in patent enforcement should causally lead to changes in firms' ability to attract debt.

Our empirical setting is particularly suited for such an analysis, because of the strong fragmentation of the global patent system. Worldwide, countries can individually determine major aspects of their national IP and patent systems. This fragmentation impedes consistent enforcement across jurisdictions and used to be particularly strong in the EU up until the early 2000s (Hall and Helmers 2019). In such a setting, improved enforcement should have significant effects regarding the reliability of patent value by decreasing legal uncertainty.

In addition to these advantageous features, there are multiple aspects suggesting that the implementation of the Enforcement Directive is an exogenous source of variation in the legal environment of sample firms. Unlike other forms of EU law, the implementation dates of EU directives vary considerably across member states (Kalemli-Özcan *et al.* 2013). This sequential implementation is unlikely to pick up market responses, because variation in the timing is mostly attributed to differences in national legislative procedures (Christensen *et al.* 2016). Additionally, implementation decisions are made on a supra-national level, whereas individual firms' actions should be only related to specific country initiatives (Schnabel and Seckinger 2019). Finally, the Directive addresses issues of IP rights in general, while our explanatory variables capture only one specific dimension, patenting. It therefore appears implausible that countries adapt their legal framework of an entire group of rights just to target one specific dimension.

3.3 Identification strategy and econometric model

The described institutional setting allows us to estimate the causal effect of the Enforcement Directive on firms' capital structure by employing a difference-in-differences (DID) methodology that differentiates among firms' ex ante propensity to respond to the change in law. In the following, we describe the different components in detail. To start with, we use two alternative strategies to quantify the implementation of the Enforcement Directive. The first measure is a binary variable equal to one if the Directive is transposed into national legislation of the respective firms' home country, or zero otherwise. This is a reasonable proxy, since firms commonly file patents in their focal market, which is mostly their home country. Yet, to reflect the empirical fact that most patents are held across various jurisdictions and not only in their home market, we use a second specification in which we assume firms to be treated depending on the locations where their patents are active. For each patent and year, we calculate the fraction jurisdictions that already implemented the Directive and aggregate values for all patents within a portfolio. If not indicated otherwise, we use this measure as our reference specification. This measurement approach is beneficial, because it mitigates endogeneity concerns even further. The complexity of legal procedures and the associated time lags make it implausible that firms designate their patents to specific jurisdictions in anticipation of a potentially beneficial but uncertain, future policy change. Figure IA3 (Internet Appendix B) displays the average values of the treatment variable across time illustrating the staggered nature of the identifying event.

In our setup, all firms are subject to the change in law, as it is not specifically

targeted at any subgroup. For identification, we therefore utilize variation across and within countries. The baseline setting exploits cross-country variation in the country-specific implementation dates. For example, Denmark, Italy, and the United Kingdom implemented the Enforcement Directive already in April 2006, whereas Sweden passed the amendments through domestic legislation three years later (see Table IA6 in the Internet Appendix A). We address concerns regarding the timely proximity of the implementation dates in Section 4.2 by deploying more granular country-level variation arising from the different degrees to which countries amend domestic legislation.

The main source of within-country variation are firm-level differences in patent portfolio values prior to the legal amendment. We assume that firms with more valuable portfolios are disproportionally affected from the Enforcement Directive. In baseline estimations, we therefore categorize firms with an above- (below-) median portfolio value during the pre-treatment period as treated (control) group. For determining this, we use both portfolio value measures separately. Further tests explore more granular variation by additionally differentiating among firms' industry-specific degree of competition prior to the change in law (see also Section 4.2). As an alternative specification in Section 4.3.1, we deploy our DID setting on a matched sample of patenting (treated) and non-patenting (control) firms.

The panel structure of the data allows us to control for unobserved heterogeneity across firms and the cyclicality of lending patterns by including firm- as well as country-time fixed effects. Moreover, all estimations measure the impact of the patent portfolios lagged by one year $(t-1)$ on firms' debt use one period later (t). As time-varying control variables, we include well-established capital structure determinants (Graham and Leary 2011): i) size, ii) profitability, iii) share of tangible assets, and iv) cash flow as defined in Table 3, Panel B. For measuring the dependent variable, we follow Rajan and Zingales (1995) and calculate firms' capital structures as total long-term debt over total capital. Long-term debt is defined as loans and liabilities with a maturity of more than one year. Our main analysis will show that the key results are not sensitive to using alternative definitions of debt-ratios. We cluster standard errors at the firm level:

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

where φ_i and δ_{ct} are firm- and country-year fixed effects. CS_{it} is a vector of the capital structure determinants and $\textit{Debt-ratio}_{it}$ measures the long-term debt ratio of firm i at the end of period t. $Value_{it-1}$ describes either one of our patent portfolio value measures of firm i as defined in Equations (1) and (2). $\textit{Post}_{ct}$ is the treatment variable and

measures the adoption of the Enforcement Directive as described above. Moreover, the dummy variable $Affected_i$ indicates whether the average portfolio value for all periods in which $Post_{ct} = 0$ is above the pre-treatment median or not. To ease consistent interpretation and if not indicated otherwise, we refer in our results to specifications that use the patent cost measure from Equation (2) for defining affectedness. The coefficient of interest, α_1, estimates the effect of the interaction of $Affected_i$ and $Post_{ct}$, which resembles the average treatment effect capturing the additional impact of the Enforcement Directive on affected firms' debt-ratios. In the following, we will refer to α_1 and equivalent coefficients as the 'DID estimator'.

3.4 Patents and debt: Descriptive analysis and stylized facts

As a basic assessment of this strategy, descriptive statistics in Table 4 compare the use of debt before and after the implementation of the Enforcement Directive, distinguishing among firms with ex ante high or low patent portfolio values. Firms with an ex ante high value patent portfolio increase their debt ratios by 15% to 18% (2.0 to 2.3 percentage points), using both portfolio value measures as defined in Equations (1) and (2). The differences in means are significant at the one percent level. In contrast, changes in debt-ratios for firms with patent portfolios of low ex ante value are much smaller and statistically insignificant. Furthermore, affected and control groups do not differ with respect to the capital structure determinants profitability and cash flows but regarding size and tangibility (see Table IA7, Panel A, Internet Appendix A). However, these differences are relatively small in economic terms, size (+8%) and tangibility (+4%), stable over time (see Panel B of Table IA7), and are thus unlikely to invalidate our empirical strategy. Still, in Section 4.3, we will address concerns regarding these differences in observable firm characteristics.

- Insert Table 4 here -

A central assumption in our main analysis is that both affected and control group firms have comparable debt capacities in the absence of the treatment, while differing in its presence. We therefore analyze whether firms with high and low ex ante patent portfolio values exhibit similar pre-treatment trends in debt ratios in several different ways. We first estimate regressions using the pre-treatment periods as relevant time windows. Regressions are specified equivalent to the baseline setup in Equation (4) but additionally include country-specific time dummies for each year preceding the initiation of the Enforcement Directive as well as their interactions with the *Affected* indicator.

Figure 4 plots the coefficients of these interactions and their corresponding 95 percent confidence intervals. The intuition is that statistically significant coefficients indicate the deviation of pre-treatment trends in firms' debt capacity. However, for both portfolio value definitions (Panel A and B), none of the coefficients are statistically significant. Estimates displayed in Table IA8 (Internet Appendix A) show that this finding is not sensitive to applying different treatment specifications.

- Insert Figure 4 here -

As a final test, we repeat the baseline regressions on the time window prior to the treatment, including a time trend variable (i.e., a running year count) and its interaction with the *Affected* variable (Table IA9 in the Internet Appendix A). Estimates on these interactions are insignificant, which confirms our previous findings by suggesting common pre-trends for affected and control group firms. Across a variety of tests, we can thus reject the hypothesis that high and low patent portfolio value firms follow different paths during the pre-treatment period.

4 Empirical results

4.1 The Enforcement Directive and debt financing

We start by analyzing the effects of the Enforcement Directive on firms' debt capacity depending on the ex ante value of respective firms' patent portfolios estimating Equation (4). Table 5 displays results on different variants of the main specification and suggests a disproportional positive effect of the Enforcement Directive on the debt ratios of firms with high patent portfolio values prior to the change in law. Across all specifications, coefficients of the DID estimators are positive and highly significant. Moreover, the effects are also sizable in economic terms. For example, the coefficient from the DID estimator of our reference specification in Column VI suggests an additional increase in debt ratios of 17% for the average affected firm relative to control group firms. Results are similar in significance and magnitude when using patent stock (Equation 1) as proxy for patent portfolio values and they are robust to using alternative definitions of the key variables (see Panels A-C of Table IA10 in the Internet Appendix A).

To ease the interpret of patent costs, we estimate specifications that use the time-variant measure of patent portfolio values instead of the indicator variable (Columns IV and VIII). This approach allows us to assign Euro values to the baseline results. Consistent with the baseline estimates, the coefficients of the interaction terms are positive

and significant at the one percent level for both portfolio value definitions. The DID estimator from Column VIII (3.513) implies that a one standard deviation increase in patent costs translates to an 8% (1.2 percentage points) increase in debt ratios for firms with ex ante high value portfolios relative to those with initially low portfolio values. Importantly, this coefficient suggests that moving an average firm from the 50th to the 75th percentile of the patent cost distribution resembles an increase of about 18,000 Euros in annual patent costs. This change in portfolio costs implies a 20% increase in debt ratios and translates to an increase in external debt of 130,000 Euros.[10]

- Insert Table 5 here -

Next, we decompose the patent portfolio value measures into its components to investigate the role of patenting on firms' debt capacity in more detail. Figure 5 plots the DID estimators from regressions that are equivalent to the baseline specification for different portfolio value definitions. We compare the coefficients for patent portfolio values as defined in Equations (1) and (2) from the first two rows to results for the coefficients on broader measures of firms' patenting activities. We first split the patent stock variable into its single components, which are the number of active patents (third row) and the number of designated jurisdictions (fourth row). The point estimates are positive and significant but they are much smaller and less precise compared to their combined use (first row). This suggests that size and value are important complements for the effect of patenting on firms' ability to attract debt. Finally, in the fifth row, we consider patent filings as the relevant patenting dimension to categorize firms into affected and control groups. Here, firms are considered to be affected by the Directive if they file at least one patent during the year preceding the change in law. The DID estimator is small and insignificant, which suggests that patent filings are not able explaining the main results. As a robustness check in Table IA11 (Internet Appendix A), we estimate the exact timing of these effects by including a set of year dummies interacted with the *Affected*-indicator from Equation (4). Using the portfolio value measures, point estimates become larger and increasingly precise as the treatment unfolds, whereas estimates for the alternative measures are much weaker or insignificant. Overall, these analyses illustrate not only the complementary effect of patent portfolio value and portfolio size but

[10]The median firm holds 650,000 Euros of debt. Hence, the multiplying effect of patenting expenses equals approximately seven when moving this median firm from Q50 to Q75 in the patent cost distribution. Conversely, moving the median firm from Q50 to Q25 reduces annual patenting costs by 6,000 Euros and lowers debt by 55,000 Euros, which implies a multiplier of about nine. The difference in these multipliers suggests a non-linear relationship between firms' patent portfolio values and their ability to attract debt. For simplicity, these calculations assume a symmetric increase in debt-ratios and debt holdings of affected firms.

also suggest that establishing a link between firms' patenting activities requires the use of more sophisticated patent measures, such as ours.

- Insert Figure 5 here -

To understand the timing of the main effects better, we investigate their lag structure by deploying an event-study design. Figure 6 presents graphical results by plotting interactions of the *Affected*-indicator with year dummies using a symmetrical time window of six years around the country-specific adoption of the Enforcement Directive (the figure notes display the regression specification). Confirming our previous results, estimates in the pre-treatment period are small and insignificant for all firms irrespective of their ex ante patent portfolio value, while differing in the post-treatment phase. The point estimates for firms with high ex ante patent portfolio values turn positive, increase over time and are statistically significant. In contrast, throughout the entire time window all estimates are insignificant for firms with low portfolio values. Thus, the paths of treated and control groups clearly diverge after the treatment occurs while moving in parallel before. Figure IA4 (Internet Appendix B) shows that this pattern is robust to using both portfolio value measures as defined in Equation (1) and (2).

- Insert Figure 6 here -

As another robustness check, we address one remaining methodological issue: When using two-way DID models with varying treatment over time, our econometric approach produces estimates that are weighted by the conditional variance in treatment (Goodman-Bacon 2021). This implies that early-adopting member states eventually have higher weights than others. We test whether this confounds our main results by repeating the main estimations but exclude early-adopting firms, i.e., firms that are treated before 2007, and by conducting a Goodman-Bacon decomposition that effectively re-weights observations. Both approaches (unreported) yield very similar estimates compared to those reported in the main analyses.

4.2 Exploiting heterogeneity in treatment intensities

In this section, we test country- and industry-specific heterogeneity regarding the intensity of the treatment. While our main analysis in Section 4.1 assumes homogeneous treatment across EU countries, the following analyses relax this assumption. Hence, exploring additional variation is important, first, because it addresses identification concerns and, second, because it delivers further important insights on the role of firms'

patenting activities to attract debt.

Different degrees of legislative changes: In a first set of tests, we exploit country-specific variation in the expected impact of the Enforcement Directive. The heterogeneous level of patent right enforcement prior to the adoption of the Enforcement Directive indicates that different EU member states most likely amended their domestic legislation to different degrees. To study this, we assess an extensive evaluation study of the Enforcement Directive by Petillion (2019), which is a collection of country-specific analyses from lawyers in each individual EU member state. We examine the extent of changes made to each national legislation based on these reviews. Specifically, for each relevant Article of the Enforcement Directive,[11] we differentiate among three categories: The text explicitly mentions that i) no changes have been made towards meeting the requirements of the Directive, ii) small adjustments were made, implying that the legislative setting is at least partially based on the pre-Directive legislation, and iii) amendments were introduced that substantially impacted legislation or legislation was newly added. Based on this, Figure 7 displays the actual amendments made by each EU member state in an Article-amendment matrix (in Panel A) and illustrates the heterogeneity in adjustments (in Panel B). This approach is appealing, because it captures the relatively high degree of fragmentation across European jurisdictions prior to the Enforcement Directive's implementation. Thereby, it documents the heterogeneous degrees of change to the national legislative systems.

- Insert Figure 7 here -

Moreover, these heterogeneous degrees can be used as an additional source of country-specific variation, testing the validity of our empirical strategy. We explore this by considering the number of actual amendments to national legislations and expect effects to be particularly pronounced in countries with a larger number of adjustments. To categorize their degree of adjustment, countries are considered as highly, moderately, or weakly affected if they implemented at least eight, seven, or at most six of the relevant Articles stipulated by the Enforcement Directive. This way, the moderately affected group resembles the median value of legislative changes among all EU15 countries.[12]

In Table 6 Panel A, we separately estimate the baseline regression (Equation 4) for these three categories. For each category, DID coefficients are positive and suggest

[11] Out of the 22 Articles, we consider all Articles as relevant which are not of administrative nature explaining formalities (Articles 1-3 and Articles 16-22) or that are suggestions (Article 12).

[12] Further, this split assures comparable sizes of the subsample. Using more granular sample splits leads to comparable point estimates in terms of size and significance.

an enhancing effect of the Directive across all countries (Columns I-III). However, the estimates vary strongly regarding their magnitude and precision. For countries with a high number of amendments, the DID coefficient is relatively large (5.776) and significant at the one percent level, whereas for countries with relatively fewer changes, coefficients are much smaller (2.635 and 0.448). For weakly affected countries, estimates are not statistically significant. This pattern is robust to using a different treatment definition (Columns and V-VII) or econometric model, i.e., using triple interaction terms (Columns IV and VIII). Findings therefore confirm that the impact of the Enforcement Directive varies depending on the country-specific intensity of the treatment, i.e., the number of the amendments to the legislative system.

- Insert Table 6 here -

Competition-induced responsiveness: The second test introduces industry-specific variation in the expected impact of the Enforcement Directive. It builds on the idea that amendments in patent enforcement law have different effects depending on firms' level of competition prior to the change in law. This is line with previous literature (e.g., Aghion *et al.* 2015) which suggests that a strengthening of patent enforcement should be most relevant for firms operating in more competitive environments, because firms' incentives to engage in costly innovation strongly depend on the additional expected returns when escaping their competitors.

We follow Aghion *et al.* (2005) by estimating industry mark-ups to approximate firms' competitive environment: Higher mark-ups imply indicate stronger market power and thus imply a weaker competitive environment and vice versa. Evidently, firm-level mark-ups and innovative activities are mutually related. To address this issue, we rely on industry-level information, because changes in individual firm characteristics are less likely to affect measures on an aggregate level. More specifically, we calculate annual firm-level mark-ups and compare them with the country-specific, pre-treatment industry average using out-of-sample data, i.e., for the universe of ORBIS firms: $\mu_{it} = \frac{sales_{it}}{opex_{it}}$, where μ_{it} are mark-ups of firm i in year t, $sales_{it}$ are the total sales during the period, and $opex_{it}$ are total operating expenses of respective firms. This variable allows us to determine whether a given sample firm faces high or low competition by comparing sample firms' mark-ups to the country- and industry-specific average mark-up that is calculated using the full ORBIS database. We measure all mark-ups during the final, country-specific year before the Enforcement Directive implementation. We classify individual firm's environment as highly (weakly) competitive, if the firm's mark-ups lie

below (above) the country-industry average mark-up.

As an initial step, we separately run the baseline specification (Equation 4) for different industry classes using the main NACE categories, which is the highest level of industry-level aggregation. Figure 8 displays the DID coefficients of the eight largest industries from our sample in the order of their average pre-treatment mark-ups (from lowest to highest competition): Real Estate Activities (L, 1.361), Professional, Scientific and Technical Activities (M, 1.246), Administrative and Support Service Activities (N, 1.176), Information and Communication (J, 1.152), Construction (F, 1.107), Agriculture, Forestry and Fishing (A, 1.081), Manufacturing (C, 1.076), and Wholesale and Retail Trade (G, 1.051). Consistent with Aghion *et al.* (2015), point estimates are positive and significant only for industries with relatively high levels of competition, while being small and insignificant for industries with weak competition.

- Insert Figure 8 here -

To gain a more detailed perspective, we calculate the thresholds for high and low competitive environments using lower levels of industry aggregation, i.e., on the 4-digit NACE level. We calculate country-industry averages and split the respective distributions into three equally-sized groups. This allows us to classify whether firms operate in high (tercile 1), medium (tercile 2), or low (tercile 3) competitive environments prior to the treatment. For each group, we run separate estimations equivalent to our baseline setting (Equation 4). Estimates are largest for firms in industries with the highest levels of competition, while becoming smaller as competition decreases (see Table 8, Columns I-III). This pattern applies across different model specifications and variable definitions.[13] Hence, results show that the propensity to respond to the Enforcement Directive increases with stronger ex ante competition and confirm that the strength of the patent system affects the relationship between competition and patenting activities. Importantly, the above findings emphasize the consistency of our empirical strategy.[14]

4.3 Testing potential threats to identification

4.3.1 CEM matching approach: Patenting versus non-patenting firms

Next, we introduce an alternative estimation approach in which we match patenting firms from the main sample with non-patenting, out-of-sample firms. For identification,

[13]This is robust to using different sample splits (i.e., quartiles and quintiles), lengths for defining the pre-treatment period (i.e., up to four years), and industry aggregations (i.e., 2-digit NACE codes).

[14]For further supportive evidence on this, Internet Appendix E provides heterogeneity analyses on industry and patent characteristics that have a plausibly higher propensity to respond to the treatment.

our baseline approach explores variation in ex ante portfolio values within patenting firms. Unlike this, the matching approach aims to obtain a control group of firms which is equivalent along observable firm characteristics but for which the Enforcement Directive was not relevant. Intuitively, exogenous variation in patent enforcement should be significantly less relevant for non-patenting firms compared to the average patenting firm. This approach helps us to show that observed differences between firms with high and low patent portfolio values (i.e., Table 4) are unlikely to drive our main findings.

We obtain potential matching candidates from the original ORBIS dataset and selecting relevant non-patenting firms using Coarsened Exact Matching (CEM) as proposed in Blackwell *et al.* (2009). CEM groups patenting and non-patenting firms according to pre-defined matching characteristics. We impose firm pairs to share the same country and industry (NACE Rev. 2 main category) and match based on the pre-treatment mean values of firm-level capital structure determinants (see Table 3), debt-ratios, and age categories.[15] This approach eventually results in a sample of 17,708 firm-year observations out of which 8,389 (9,316) observations are from patenting (non-patenting) firms. Summary statistics in Table 7 show that patenting and matched non-patenting firms are comparable along all relevant dimensions.

- Insert Table 7 here -

We estimate the following regression equation, which explains the effect of the Enforcement Directive on the debt rations of patenting firms relative to the matched control group consisting of non-patenting firms:

$$\textit{Debt-ratio}_{it} = \gamma_1 Patenter_i + \gamma_2 Post_{ct} + \gamma_3 (Patenter_i \times Post_{ct}) + \gamma_4 CS_{it} + u_{it} \ , \quad (5)$$

with the dummy variable, $Patenter_i$, indicating whether firm i belongs to the group of ex ante patenting firms, or not. The remaining variables are specified as defined in Equation (4). Hence, the DID estimator, γ_3, is the coefficient of interest and captures the additional effect of the Enforcement Directive on the debt-ratios of patenting firms relative to non-patenting firms.

Table 8 contains results from estimating Equation (5) as well as alternative model specifications. The coefficient of the DID estimator is positive and significant, suggesting that patenting firms disproportionally increase their debt ratios relative to non-patenting

[15] The eight age categories are: $\leq$2, 3-5, 6-10, 11-15, 16-25, 26-50, 51-100, and >100 years, respectively. For the non-categorical matching variables, we use 30 equally sized bins. Whenever observations fall into bins without closest neighbor, they are not considered for a match.

firms with the onset of the treatment. This effect is economically significant and robust to applying a rich set of fixed effects. The point estimate on the coefficient of interest in Column III implies that the average ex ante patenting firm increases its debt-ratio by about 17% (or 1.7 percentage points) relative to the non-patenting group. Insignificant estimates on the components of the DID estimator show that being a patenting firm has no effect on the use of debt, per se. Similarly, the implementation of the Enforcement Directive by itself does not explain changes in debt ratios. These findings are consistent with the empirical strategy of our matching approach, as they provide strong evidence that firms only respond to the patent-related legal change if patenting is a relevant business strategy for them. Further, results are in line with baseline estimates, which is important as it mitigates concerns that observable differences in firm characteristics drive the main results.

- Insert Table 8 here -

4.3.2 Robustness tests: announcement effects and the Financial Crisis

Announcement effects: Our empirical strategy assumes that effects should be observable once the Directive becomes effective and not when it is announced. This is consistent with prior literature finding that dynamics in the strength of the IP system originate from the actual implementation and enforcement but not from the confirmation of the change itself (Papageorgiadis and Sofka 2020). The Enforcement Directive was finalized and published on April 29th, 2004 by the European Parliament and the Council, whereas it became effective at different points in time across EU member states throughout the subsequent five years. To investigate whether the announcement of the Enforcement Directive already had an effect on firms' debt capacity, we exchange the treatment variable indicating the actual implementation of the directive with a placebo indicator equal to one for all years starting with 2004 and zero otherwise.

Table 9 first displays estimations using the full sample (Columns I-IV). Point estimates on the DID estimators are positive and significant to varying degrees, but they are substantially smaller and less precise compared to the baseline results. Moreover, obtaining positive estimates is not surprising, given that the artificial treatment period includes years from the true treatment period. Hence, to gain a better understanding on the announcement effect, Columns V-VIII display results from estimations in which all country-specific post-treatment years are excluded (i.e., in which $Post_{it} > 0$). The idea is that the potential effects of the Directive's announcement should be measurable already during the years between its announcement and implementation. However, across

specifications DID estimates are statistically insignificant suggesting that the announcement of the Enforcement Directive did not have a significant impact on firms' use of debt. Taken together, these findings support our measurement approach with respect to the timing of the treatment.

- Insert Table 9 here -

Financial Crisis effects: Since the treatment period encloses the Global Financial Crisis, which unfolded in late 2008, it is important to investigate its effect on the main results. If inventive activities were related to the financial health of respective companies, firms with high patent portfolio values during the mid-2000s could have attracted disproportionally more debt over the course of the crisis. We thus analyze whether the Global Financial Crisis is a distinct driver for the main estimates in multiple ways. In a first approach, we alter our baseline specification by adding a crisis treatment variable and its interaction with the *Affected* indicator from Equation (4). The intuition behind this is similar to a placebo analysis: If the crisis is indeed better at explaining the main results, we would expect to obtain larger - or at least equally sized - point estimates relative to the original DID estimator (i.e., α_1 in Equation 4). We operationalize the crisis by using a dummy variable ($crisis_{ct}$) that equals one if the home country c of a firm experiences a recession in period t. We follow Laeven and Valencia (2013) by assuming that countries face a recession once real GDP growth is negative and unemployment rates increase for at least two consecutive quarters. Table 10 displays estimates of this test using various model specifications. Results are unambiguous, as coefficients of the interaction terms that use the crisis as the treatment variable are small and insignificant across all specifications. In contrast, the original DID estimators remain large, positive, and significant at the one percent level.

- Insert Table 10 here -

As robustness tests, we repeat the estimations of Equation (4) but use the Global Financial Crisis as a treatment event (see Table IA12 in the Internet Appendix A). First, we exchange the treatment variable with a set of country-specific crisis indicators (Columns I-IV) and obtain positive coefficients on DID estimators, which are statistically significant in some cases. In general, this is a plausible finding, because the timing of the treatment and the crisis overlap. Notably, however, the magnitude and level of significance of estimates are substantially smaller compared to the baseline scenario. To verify this, we use an alternative crisis measure, which is a binary indicator variable that equals one for the years after 2008, which is typically associated with the onset of

the crisis. We then exclude country-specific years in which the economy went to full recovery to isolate the effect during the crisis. Results in Columns V-VIII are even weaker compared to the first set of estimates and underline the findings from Table 10.

Based on this first set of tests, it appears unlikely that the main effects can be predominantly associated with the Global Financial Crisis, even though the main effects are centered around the years of the crisis. As a final plausibility check on the effects of the crisis, we test the extent to which survivorship biases our results. This is important, because the effects might as well be confounded from the ensuing period of recovery and not the recession itself. We therefore address the concern that the main results might be driven by construction, which would be the case if the crisis screens out underperforming firms with lower debt capacities.

ORBIS data does not contain information on insolvencies. However, we observe 80% of sample firms in each year between 2007 and 2012. This is useful, since we can infer with certainty that these firms survived the crisis. The underlying assumption is that effects are more pronounced for a sample of surviving firms compared to estimates on the full sample, only if surviving firms were indeed driving our main results. Hence, we repeat the baseline regressions for the subsample of firms that are observed at least five times between 2007 and 2012. Figure 9 displays the results graphically, following the specifications of Figure 5. All coefficients on the DID estimators are very similar both in magnitude and significance. This pattern is consistent across different patenting definitions and shows that results are not different for firms that survived the crisis. Overall, the various analyses in this section emphasize that our main results are unlikely to be driven by alternative factors arising from the Global Financial Crisis.

- Insert Figure 9 here -

4.3.3 Testing firm-level characteristics: Firm size and asset tangibility

As a next step, we focus on the underlying firm-level characteristics that may determine the sorting of firms into their ex ante patent portfolio values. Evidently, firm size and the number of actively held patents are positively related. While our measures move far beyond simple patent counts, it is still important to test the effect of firm size for our main results. In a series of robustness tests, we therefore add different firm size measures interacted with the treatment variable to the specifications from Equation (4). Estimates displayed in Table IA13 (Internet Appendix A) confirm our main results.

Since this does not necessarily provide insights on heterogeneous treatment effects associated with differences in firm size, we separately examine regressions for different

size classes. We split the sample according to firms' average number of employees during the pre-treatment period and categorize firms with less than 100 employees as small, firms with 100-500 employees as medium-sized, and firms with at least 500 employees as large. Figure 10 displays the DID-estimators of these regressions. The DID estimators for medium-sized firms are largest and significant, whereas the estimators of small firms are also positive, sizable and (partially) significant. In contrast, for large firms DID estimators are smallest and insignificant.[16] Further, the overall pattern is consistent with estimates from Table IA13 (Internet Appendix A) and shows that large firms are unlikely to account for the main findings. Instead, effects are more pronounced for smaller firms, while being strongest for medium-sized firms.

- Insert Figure 10 here -

As a next step, we analyze the role of tangible assets for innovative firms to secure debt. Plausibly, tangible assets may serve as a complement for the use of intangible property for attracting loans. For example, in baseline regressions (see Table 5) coefficients of the control variable *tangibility* are persistently positive and significant, indicating the importance of tangible assets in our setup. An alternative hypothesis could therefore be that high asset tangibility is a necessary condition for firms to deploy their patent portfolios in borrowing activities.

To study the role of tangible assets, we split the sample into quartiles regarding the average pre-treatment tangible asset ratio distribution, to distinguish firms with high (Q4), medium (Q2 and Q3), and low (Q1) ex ante tangibility. Table 11 (Panel A, Columns I-III) shows that positive effects from the baseline regressions hold across categories. However, while results are (weakly) significant for firms with high or medium tangibility they are insignificant for firms with low tangibility. To test the robustness of these results, we add a specification that includes triple interactions of the original DID estimators interacted with a dummy indicating whether firms have particularly high or low tangibility (Panel A, Columns V-VII). While coefficients on the high (low) triple interaction terms are positive (negative), none of the estimates is statistically significant. This suggests that having particularly high tangibility does not have an additional effect on debt ratios. Still, the lack of significance of the estimates for firms with few tangible assets suggests that a certain level of complementary tangible assets is indeed relevant for establishing the positive link between patenting on debt financing.

[16] Differences in the magnitude of the coefficients cannot be explained by differences in the dependent variable across firm size categories. Small and medium-sized firms have comparable debt-ratios relative to large firms (14.2% versus 14.1%, t-value 0.21), such that point estimates can be directly compared.

- Insert Table 11 here -

Literature shows that more mature and thus larger firms are more likely to have accumulated tangible assets (e.g., Berger and Udell 1998). In fact, the average share of tangible assets over total assets is significantly higher for large firms compared to smaller firms in our sample (25.6% versus 21.5%, t-value 17.28). To further assess the possibility of a complementary effect of asset tangibility in combination with firm size, we separately repeat the analysis from Panel A in Table 11 for small and medium-sized firms (Panel B) and for large firms (Panel C). Confirming the above findings, effects for small and medium-sized firms are positive and statistically significant, while being small and insignificant for large firms. Estimates for small and medium-sized firms follow a very similar pattern compared to estimates on the full sample (Panel A). This is generally consistent with the notion of a complementary use of tangible assets and patents. However, the effects are not very robust and only apply for relatively smaller firms. Overall, the results in this section allow us to reject the competing hypothesis that the availability of tangible assets or firm size are omitted factors that determine the effects of firms' patenting activities on their use of debt. In contrast, findings can be interpreted such that the main results are attributed to an average firm, which is medium-sized and holds an average level of tangible assets.

5 Borrowing against patents and financing conditions

5.1 Do valuable portfolios help financially constrained firms?

In this section, we examine the effect of the Enforcement Directive and firms' patent portfolios for the debt capacity of financially constrained firms. This is particularly important, since isolating the effect for ex ante constrained firms sheds new light on the potential role of intellectual property to mitigate financing constraints for innovation-intensive firms. In addition to this, distinguishing between constrained and unconstrained firms serves as a plausibility test: Economic theory suggests that shocks to external funding have more pronounced effects if financing frictions are present (e.g., Holmström and Tirole 1997) and, hence, it is reasonable to expect heterogeneous effects depending on firms' financing conditions.

As a first approach, we propose that publicly listed firms are less likely to be financially constrained, since the availability of a broader set of financing sources, such as access to capital and bond markets, is found to make public companies less dependent on debt financing (Freixas and Rochet 2008). This is an observation confirmed in our

sample, where debt ratios for private firms are significantly higher than those of listed firms (18.6% versus 15.2%, t-value 6.58). In line with this, the positive effects of the Enforcement Directive on firms' debt capacity should be disproportionately higher for private firms as compared to listed companies. We test this by re-estimating the baseline specification on split samples for private and publicly listed firms. Across multiple specifications displayed in Table IA14 (Internet Appendix A), the estimates for private firms are large and significant, while being small and insignificant for the subset of public firms. This suggests that the enhancing effect of valuable patent portfolios for firms' debt capacity is more important for firms without access to public stock markets, i.e., for more financially constrained firms.

We now turn to alternative constraint measures, to account for the fact that stock market participation is a rather rough measure of financing constraints. Specifically, we consider the RZ-score (see Rajan and Zingales 1998) which measures the degree of dependence on external finance by relating firms' capital expenditures ($Capex$) to their cash flows (CF): $(Capex - CF)/CF$. Higher values imply that firms are less likely to cover their investments in fixed assets with internal funds and therefore have a higher demand for external finance. To avoid potential issues by selecting specific financing constraints measures, we additionally use the more generally applicable S&A index (see Hadlock and Pierce 2010) for identifying constrained firms. Here, the intuition is that firms in the earlier phases of their life cycle are particularly constrained in their access to different financing sources, whereas this restriction vanishes as firms mature.

For both measures, we do not consider the precise score for determining firms' constraints, but consider the industry-specific distribution of the respective scores at the final, country-specific year prior to the Enforcement Directive adoption. We classify firms as being financially constrained, if they score above the respective median value and vice versa. These two aspects mitigate concerns regarding endogeneity of the classification and regarding the precision of the selected measures.

Table 12 displays regression estimates explaining debt ratios of ex ante financially constrained (Columns I-III) and unconstrained (Columns IV-VI) firms. Panel A uses the RZ-score and Panel B uses the S&A index as proxy financing constraints. Both measures provide a very consistent picture across different regression specifications. The DID estimators are large and statistically significant for the subset of ex ante financially constrained firms, whereas estimates are only partly significant and small in magnitude for unconstrained firms. This underlines our first findings regarding firms' stock market participation and shows that the positive effect of the Enforcement Directive for firms

with valuable patent portfolios is disproportionately high for firms with a higher dependence on external financing. Hence, our results suggest that utilizing patent portfolios may help innovative firms to alleviate financing constraints.

- Insert Table 12 here -

5.2 How do valuable portfolios help financially constrained firms?

As a final step of the empirical analysis, we investigate a potential channel how valuable patent portfolios support debt financing activities. Specifically, we test whether the Directive affects the interest expenses of firms depending on their patenting activities. The intuition of this is that, ceteris paribus, stronger patent enforcement may lower the risk associated with a patenting firm that seeks debt financing, in particular, for those firms with relatively valuable patent portfolios. Since the price of a loan resembles the underlying risk associated with a borrower, the decreased risk should be reflected in lower costs of obtaining external debt financing. For measuring these costs, we calculate firms' annual interest burden, which we define as the total of interest expenses within a year as a fraction of the average long-term debt held during the period.[17]

Panel A of Table 13 illustrates the properties of the interest burden variable and compares firms' pre- and post-treatment averages. With an average decline of 0.17 percentage points (significant at the five percent level), interest expenses become slightly smaller for all firms. However, distinguishing among firms with high and low ex ante patent portfolio values shows a very clear pattern. For firms with low portfolio values, the difference of 0.07 percentage in interest expenses is statistically not significant and indicates that the cost of debt for these firms are not affected. In contrast, for firms with valuable patent portfolios the average decline in interest rates much larger (0.38 percentage points) and significant at the one percent level.

- Insert Table 13 here -

Following this, in Panel B of Table 13, we estimate the effect of the Enforcement Directive on the interest burden of high patent portfolio value firms and, in particular, on those firms that benefited from the adoption of the change in law. We augment our baseline estimations defined in Equation (4) by adding a triple interaction term of the

[17] Average debt holdings is calculated as the unweighted mean of long-term debt at the beginning and the end of each period. We use this approach, since our sample does not comprise individual loan-level information and, hence, interest rates. We take into account all financial charges of a given year and thus tend to overestimate interest payments that arise from firms' external debt holdings. Hence, if anything, this approximation should lead towards underestimating the effect of patenting on firms' interest rates. In robustness tests, we also use the logarithm of total interest expenses.

DID estimator interacted with a dummy that equals one for firms which benefited from the policy amendment. In line with the results from our main part, these are firms that fulfill two criteria: i) they were ex ante financially constrained and ii) they increased their debt ratios over the course of the Enforcement Directive adoption process. The triple interaction term therefore captures the additional effect of the strengthening in patent enforcement for these firms, given they had a valuable patent portfolio. Intuitively, the effects of the change in law on firms' costs of obtaining debt should be associated with this particular group.

A series of results confirms these considerations (Table 13, Panel B). Whereas coefficients on the DID estimator and patent value variable are negative but statistically insignificant (Columns I), estimates are negative, large, and statistically highly significant for the triple interaction terms (Columns II-IV). The estimates are robust to using all three definitions of financing constraints that were applied in Section 5.1, i.e., the ex ante RZ-scores, S&A index values, and a dummy that equals one for private firms (Columns II, III, and IV, respectively). Further, the effects are sizable in economic terms. Point estimates of the triple interaction terms suggest an average, additional decrease in annual interest burden between 19 and 28% (1.7 and 2.5 percentage points) for affected firms, whereas estimates for unaffected firms are captured by the original DID estimators and remain insignificant. These findings document the negative effect of the Enforcement Directive on the interest burden of firms that were most affected. Hence, results show that stronger patent enforcement enhances the use of debt for firms with valuable patent portfolios by lowering their cost of external debt.

6 Conclusion

Agency costs in debt financing increase refinancing costs especially for innovation-intense firms. However, these firms may actually use their intellectual property to attract debt and soften financing constraints. Our study highlights the large-scale potential of patenting activities to enhance firms' debt capacity, by showing that the improvement of patent enforcement causally results in higher debt ratios of firms with more valuable patent portfolios. We therefore provide first evidence on the impact of actively held patent portfolios on financing decisions, in particular, for a large representative sample. Our estimations show that effects are stronger for small and medium-sized firms, especially if complementary tangible assets are available. Importantly, results are most pronounced for firms with initially limited access to financing and provide first, large-scale evidence that firms' patenting activities enhances their debt capacity through mitigating financing

constraints and by lowering the cost of debt.

Moreover, our analyses introduce two novel features, which provide further insights on the relationship between patenting and debt financing. First, we develop a novel measure of firm-level patenting activities that utilizes annual patent fee payments and allows us to quantify the size and the value of firms' patent portfolios. Our approach is appealing, because it explains variation along the entire value distribution of patents while still being applicable to virtually all patenting firms irrespective of their lifecycle stage, size, or legal status. Using this measure, we demonstrate that portfolio size and portfolio value are essential complements for the enhancing effect of patenting on debt financing.

As another novel component, our analysis explores the staggered implementation of the Enforcement Directive across EU member states as an exogenous source of variation in the strength of patent right enforcement. In combination with our patent portfolio measures, this setting discloses that stronger patent enforcement can enhance firms' debt capacity. Using a difference-in-difference methodology that differentiates among firms with high and low patent portfolio values prior to the change in law, we find an additional average increase in debt ratios of 17% for firms with more valuable portfolios when comparing pre- and post-treatment levels. Heterogeneous treatment analyses show that effects are strongest for firms that are located in countries with larger adjustments to the legal system and for firms active in industries that are more competitive. The specific empirical setting thus provides new insights by illustrating that harmonized and strong patent enforcement is an important component for unfolding a positive effect of patenting on firms' debt capacity.

The above results have valuable implications from both a managerial and a governmental perspective. From a managerial perspective, our findings urge firms to consider IP-backed financing as a potential funding source. From a governmental perspective, results show that a harmonized, more reliable enforcement system boosts the potential of intellectual property rights for attracting external funding and therefore particularly benefit innovation-intensive firms.

References

Aghion, P., Bloom, N., Blundell, R., Griffith, R. and Howitt, P. (2005). Competition and innovation: An inverted-u relationship. *The Quarterly Journal of Economics*, **120** (2), 701–728.

—, Howitt, P. and Prantl, S. (2015). Patent Rights, Product Market Reforms, and Innovation. *Journal of Economic Growth*, **20** (3), 223–262.

Angrist, J. D. and Pischke, J.-S. (2008). *Mostly harmless econometrics: An empiricist's companion*. Princeton University Press.

Arora, A. and Ceccagnoli, M. (2006). Patent protection, complementary assets, and firms' incentives for technology licensing. *Management Science*, **52** (2), 293–308.

Berger, A. N. and Udell, G. F. (1998). The economics of small business finance: The roles of private equity and debt markets in the financial growth cycle. *Journal of Banking & Finance*, **22** (6-8), 613–673.

Bessen, J. and Maskin, E. (2009). Sequential innovation, patents, and imitation. *The RAND Journal of Economics*, **40** (4), 611–635.

Blackwell, M., Iacus, S., King, G. and Porro, G. (2009). Cem: Coarsened exact matching in stata. *The Stata Journal*, **9** (4), 524–546.

Chava, S., Nanda, V. and Xiao, S. C. (2017). Lending to Innovative Firms. *The Review of Corporate Finance Studies*, **6** (2), 234–289.

—, Oettl, A., Subramanian, A. and Subramanian, K. V. (2013). Banking deregulation and innovation. *Journal of Financial Economics*, **109** (3), 759–774.

Christensen, H. B., Hail, L. and Leuz, C. (2016). Capital-market effects of securities regulation: Prior conditions, implementation, and enforcement. *The Review of Financial Studies*, **29** (11), 2885–2924.

Cockburn, I. M., Lanjouw, J. O. and Schankerman, M. (2016). Patents and the global diffusion of new drugs. *American Economic Review*, **106** (1), 136–64.

Conti, A., Thursby, J. and Thursby, M. (2013). Patents as signals for startup financing. *The Journal of Industrial Economics*, **61** (3), 592–622.

de la Potterie, B. v. P. (2010). Patent fixes for Europe. *Nature*, **467** (7314), 395.

de Rassenfosse, G. and Jaffe, A. B. (2018). Are patent fees effective at weeding out low-quality patents? *Journal of Economics & Management Strategy*, **27** (1), 134–148.

Deutsche Bundesbank (2020). Exchange rates, euro foreign exchange reference rates, gold prices. `https://www.bundesbank.de/en/statistics/time-series-databases`, (accessed: 20/03/2020).

EPO (2018). Inventors' Handbook. `https://www.epo.org/learning-events/materials/inventors-handbook.html`, (accessed: 03/02/2018).

European Commission (2000). *Communication from the Commission to the Council and the European Parliament. Follow-up to the Green Paper on combating counterfeiting and piracy in the single market.* Tech. Rep. COM(2000) 789.

European Commission (2003). *Proposal for a Directive of the European Parliament and of the Council on Measures and Procedures to Ensure the Enforcement of Intellectual Property Rights.* Tech. Rep. COM(2003) 46.

European Union (2017). Support study for the ex-post evaluation and ex-ante impact analysis of the IPR Enforcement Directive. *EU publications*, (ET-06-17-131-EN-N).

Eurostat (2018). Eurostat indicators on High-tech industry and Knowledge-intensive services. `https://ec.europa.eu/eurostat/cache/metadata/Annexes/htec_esms_an3.pdf`, (accessed: 10/15/2018).

Farre-Mensa, J., Hegde, D. and Ljungqvist, A. (2020). What Is a Patent Worth? Evidence from the U.S. Patent "Lottery". *The Journal of Finance*, **75** (2), 639–682.

Fischer, T. and Ringler, P. (2014). What patents are used as collateral? an empirical analysis of patent reassignment data. *Journal of Business Venturing*, **29** (5), 633–650.

Fleissner, P. (2009). The "commodification" of knowledge in the global information society. *tripleC: Communication, Capitalism & Critique. Open Access Journal for a Global Sustainable Information Society*, **7** (2), 228–238.

Freixas, X. and Rochet, J.-C. (2008). *Microeconomics of banking*. MIT press.

Gambardella, A., Giuri, P. and Luzzi, A. (2007). The market for patents in Europe. *Research Policy*, **36** (8), 1163–1183.

Giuri, P., Mariani, M., Brusoni, S., Crespi, G., Francoz, D., Gambardella, A., Garcia-Fontes, W., Geuna, A., Gonzales, R., Harhoff, D. *et al.* (2007). Inventors and invention processes in europe: Results from the patval-eu survey. *Research Policy*, **36** (8), 1107–1127.

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics*.

Graham, J. R. and Leary, M. T. (2011). A review of empirical capital structure research and directions for the future. *Annual Review of Financial Economics*, **3** (1), 309–345.

Graham, S. J. H., Marco, A. C. and Myers, A. F. (2018). Monetizing marks: Insights from the uspto trademark assignment dataset. *Journal of Economics & Management Strategy*, **27** (3), 403–432.

Hadlock, C. J. and Pierce, J. R. (2010). New evidence on measuring financial constraints: Moving beyond the KZ index. *The Review of Financial Studies*, **23** (5), 1909–1940.

Haeussler, C., Harhoff, D. and Mueller, E. (2014). How patenting informs VC investors–The case of biotechnology. *Research Policy*, **43** (8), 1286–1298.

Hall, B. H. and Helmers, C. (2019). The impact of international patent systems: Evidence from accession to the european patent convention. *Research Policy*, **48** (9), 103810.

—, Jaffe, A. B. and Trajtenberg, M. (2001). The NBER patent citation data file: Lessons, insights and methodological tools. *NBER Working Paper*, **8498**.

— and Lerner, J. (2010). The financing of r&d and innovation. In *Handbook of the Economics of Innovation*, vol. 1, Elsevier, pp. 609–639.

Harhoff, D. (2016). Patent quality and examination in Europe. *The American Economic Review*, **106** (5), 193–97.

—, Hoisl, K., Reichl, B. and de la Potterie, B. v. P. (2009). Patent validation at the country level—the role of fees and translation costs. *Research Policy*, **38** (9), 1423–1437.

—, Scherer, F. M. and Vopel, K. (2003). Citations, family size, opposition and the value of patent rights. *Research Policy*, **32** (8), 1343–1363.

Haskel, J. and Westlake, S. (2018). *Capitalism without capital: The rise of the intangible economy*. Princeton University Press.

Hochberg, Y. V., Serrano, C. J. and Ziedonis, R. H. (2018). Patent collateral, investor commitment, and the market for venture lending. *Journal of Financial Economics*, **130** (1), 74–94.

Holmström, B. and Tirole, J. (1997). Financial intermediation, loanable funds, and the real sector. *The Quarterly Journal of Economics*, **112** (3), 663–691.

IP5 (2018). Statistics Report 2017 Edition. `https://www.fiveipoffices.org/statistics/statisticsreports/2017edition.html`, (accessed: 03/01/2019).

Jacobs, B. W. (2011). Using intellectual property to secure financing after the worst financial crisis since the great depression. *Marquette Intellectual Property Law Review*, **15** (2), 449–464.

Kalemli-Özcan, S., Papaioannou, E. and Peydró, J.-L. (2013). Financial regulation, financial globalization, and the synchronization of economic activity. *The Journal of Finance*, **68** (3), 1179–1228.

Kerr, W. R. and Nanda, R. (2009). Democratizing entry: Banking deregulations, financing constraints, and entrepreneurship. *Journal of Financial Economics*, **94** (1), 124–149.

Kogan, L., Papanikolaou, D., Seru, A. and Stoffman, N. (2017). Technological innovation, resource allocation, and growth. *The Quarterly Journal of Economics*, **132** (2), 665–712.

Laeven, L. and Valencia, F. (2013). Systemic banking crises database. *IMF Economic Review*, **61** (2), 225–270.

Lerner, J. and Seru, A. (2021). The use and misuse of patent data: Issues for finance and beyond. *The Review of Financial Studies*.

Loumioti, M. (2012). The use of intangible assets as loan collateral. *Available at SSRN 1748675*.

Mann, W. (2018). Creditor rights and innovation: Evidence from patent collateral. *Journal of Financial Economics*, **130** (1), 25–47.

McGuire, M., von Zumbusch, L. and Joachim, B. (2006). Verträge über Schutzrechte des geistigen Eigentums (Übertragung und Lizenzen) und dritte Parteien (Q 190). *GRUR Int*, **682**.

Mes, P. (2015). Patentgesetz, Gebrauchsmustergesetz: PatG, GebrMG. *Kommentar (4. Aufl.). München: CH Beck*.

Papageorgiadis, N. and Sofka, W. (2020). Patent enforcement across 51 countries–patent enforcement index 1998–2017. *Journal of World Business*, **55** (4), 101092.

Petillion, F. (2019). *Enforcement of Intellectual Property Rights in the EU Member States*. Intersentia.

Rajan, R. G. and Zingales, L. (1995). What do we know about capital structure? Some evidence from international data. *The Journal of Finance*, **50** (5), 1421–1460.

— and — (1998). Financial dependence and growth. *The American Economic Review*, **88** (3), 559–586.

Rampini, A. A. and Viswanathan, S. (2013). Collateral and capital structure. *Journal of Financial Economics*, **109** (2), 466–492.

Saidi, F. and Žaldokas, A. (2021). How does firms innovation disclosure affect their banking relationships? *Management Science*, **67** (2), 742–768.

Schankerman, M. and Pakes, A. (1986). Estimates of the Value of Patent Rights in European Countries During the post-1950 Period. *Economic Journal*, **96** (384), 1052–1076.

Schnabel, I. and Seckinger, C. (2019). Foreign banks, financial crises and economic growth in europe. *Journal of International Money and Finance*, **95**, 70–94.

Spence, M. (2002). Signaling in retrospect and the informational structure of markets. *The American Economic Review*, **92** (3), 434–459.

Tables from the main part:

Table 1: Descriptive statistics on patenting measures

	Citations (portfolio)	Avg. citations (per patent)	Generality index	Patent costs (portfolio)	Avg. patent costs (per patent)	Patent stock
Mean	24.48	3.23	0.15	24,690.2	1,505.94	72.30
Std. dev.	132.20	3.70	0.18	157,243	987.63	357.79
Min.	0	0	0	25.67	5	1
Max.	6,048	20	0.83	9,715,573	987.63	12,930
Percentiles						
p1	0	0	0	111.42	70	1
p5	0	0	0	398.74	198.36	1
p10	0	0	0	808.11	338.33	2
p25	1	1	0	2,115.38	713.31	4
p50	5	2	0.07	5,280.00	1,400.93	19
p75	14	4.33	0.25	13,209.1	2,081.44	41
p90	39	7.50	0.44	35,810.8	2,625.53	115
p95	74	10.13	0.50	71,221.2	3,350.48	223
p99	343	20	0.66	322,024	4,729.07	949

Notes: This table provides summary statistics comparing several two common, value-relevant patent measures (citations and generality) with the two portfolio value measures introduced in Section 2. Column I and II contain the total and average number of citations of all patents in a given firm's patent portfolio. We only consider citations received within the first eight years after patent application. Column III contains the average value of respective patents' generality measure. Patent generality is computed as suggested by Hall *et al.* (2001). The last three columns contain variants of the patent portfolio value measures. Column IV contains the total costs of firms' patent portfolios as defined in Equation (2). Column V displays the average costs per patent within firms' portfolios. Column VI displays portfolio values measured by patent stock as defined in Equation (1).

Table 2: Patenting costs and their 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 portfolio 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 regression estimates explaining the relationship between patent costs and the occurrence of high impact patents. The regression equations are defined in Equation (3). The dependent variable is the top 25 (Columns I and II), 10 (Columns III and IV), and 1 percent (Columns V and VI) in the firm-year specific generality distribution. Patent generality is computed as suggested by Hall *et al.* (2001). The main regressor, patent portfolio costs, is the industry-year normalized values of firms total patent costs defined in Equation (2). Regressions include several control variables which are not displayed but their use is indicated at the bottom of the table. Regressions control for time-varying firm-specific covariates, i.e., firm size, tangibility, profitability, and cash flow ratios (see Table 3). Some specifications further 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.

Table 3: Summary statistics and variable definitions

Panel A: Descriptive statistics on key variables

Variable	Obs.	Mean	Std. dev.	Min.	Q50	Max.
Debt-ratio	44,004	18.413	25.554	0	7.209	100
Employees (#)	24,443	1,880	7,467	1	96	51,939
Age	49,634	25.5	22.5	1	18	84
Quoted	51,719	0.053	0.225	0	0	1
Firm size (log. assets)	51,719	9.203	2.772	0	8.946	19.857
Profitability (RoA)	38,824	0.083	0.222	-1.204	0.102	0.568
Tangibility	50,144	0.236	0.240	0	0.150	1
Cash flow-ratio	37,609	0.069	0.172	-0.944	0.089	0.488
Patents filed (p.a.)	51,719	0.426	3.167	0	0	144
Active patents	35,523	7.203	44.600	1	2	2,684
Jurisdictions (avg.)	35,523	11.194	9.648	1	7	37
Patent age (avg.)	35,523	4.851	8.648	0	4.852	20

Panel B: Defining capital structure determinants

Variable	Definition	Predicted impact
Firm size	$= \; log(\text{total assets})$	positive
Profitability (RoA)	$= \; \frac{\text{ebit}}{\text{total assets}}$	negative
Tangibility	$= \; \frac{\text{tangible-fixed assets}}{\text{total assets}}$	positive
Cash flow ratio	$= \; \frac{\text{total cash flow}}{\text{total assets}}$	negative

Notes: The table provides summary statistics on financial and patenting variables (Panel A) and defines the capital structure determinants (Panel B). Financial variables include general information, the main dependent variable, and the common control variables as defined in Panel B of this table. Additionally, firm-level patent information comprises patent filings per year, the absolute number of active patents held in a given year, the average number of designated jurisdictions within a portfolio, and the average patent age within a portfolio. Panel B defines the set of common capital structure determinants, including their predicted impact the firm-level use of debt (see e.g., Graham and Leary 2011). Unless explicitly stated, this set of variables is included in all regressions to account for time-variant firm-specific characteristics that affect debt-ratios. If not displayed, their use is indicated by the term *firm-level* in the footnotes of respective output tables.

Table 4: Debt-ratios before and after the Enforcement Directive's implementation

Portfolio value definition	*Affected*	Debt-ratio *Before*	Debt-ratio *After*	Difference in means (*t-values*)
Patent stock (Eq. 1)	High (= 1)	12.726	14.683	1.957 (4.502)
	Low (= 0)	15.572	16.025	0.453 (1.201)
Patent costs (Eq. 2)	High (= 1)	12.985	15.269	2.285 (5.220)
	Low (= 0)	15.439	15.541	0.102 (0.272)

Notes: The table compares mean values of sample firms' debt ratios distinguishing among firms with respect to their ex ante patent portfolio values, i.e., according to our measures of patent stock (1) and patent costs (2). Firms above the median value in the year before the treatment occurs are classified as affected. Pre- and post treatment debt ratios are compared, where before (after) denotes the firm specific pre- (post-) treatment period, i.e., once $Post > 0$ ($Post = 0$). The last column contains the differences in these mean values (t-values are displayed in parentheses below the means).

Table 5: Baseline regression: capital structure determinants and patenting

Dependent variable:	Debt-ratio							
Porfolio value definition:	Patent stock				Patent costs			
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
Affected × Post		2.528	2.655			2.462	1.534	
		(0.816)	(0.715)			(0.719)	(0.823)	
Portfolio value × Post				23.780				3.513
				(7.094)				(1.438)
Portfolio value	7.199	7.322	7.432	-2.374	0.320	0.114	0.368	-0.899
	(5.132)	(5.064)	(5.022)	(3.762)	(1.095)	(1.092)	(1.097)	(1.077)
Firm size	0.956	0.967	0.958	0.971	0.948	0.961	0.960	0.956
	(0.523)	(0.522)	(0.522)	(0.523)	(0.523)	(0.522)	(0.522)	(0.523)
Profitability	-5.470	-5.398	-5.444	-5.555	-5.404	-5.324	-5.391	-5.397
	(1.947)	(1.953)	(1.952)	(1.947)	(1.951)	(1.947)	(1.950)	(1.954)
Tangibility	15.035	15.007	15.019	15.113	15.042	14.930	14.943	15.047
	(2.033)	(2.037)	(2.032)	(2.024)	(2.035)	(2.037)	(2.037)	(2.033)
Cash flow	-11.303	-11.317	-11.279	-11.156	-11.379	-11.420	-11.373	-11.341
	(2.019)	(2.020)	(2.022)	(2.017)	(2.024)	(2.021)	(2.025)	(2.025)
Constant	1.585	1.045	0.974	1.503	1.768	1.279	1.310	1.579
	(5.240)	(5.265)	(5.229)	(4.965)	(5.254)	(5.285)	(5.244)	(5.260)
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 values on their debt ratios. The dependent variable is the debt to asset ratio. Firm-level control variables are defined in Table 3. Regressions control for unobserved heterogeneity by including firm- and country-year fixed-effects. Regressions use two alternative definitions of patent portfolio value, the patent stock (Columns I-IV) and patent costs (Columns V-VIII), included with their first lag of the normalized patent value variables. Portfolio values are defined in Equation 1 (2). Columns I and V are capital structure equations that additionally include the patent portfolio value measures introduced in Section 2. Columns II and III (VI and VII) follow the main regression specification defined by Equation (4), interacting the treatment indicator based on the pre-treatment patent stock (cost) value of firms. Regressions use the two alternative measures of treatment as defined in 3.3. Columns I and V use the continuous treatment variable. Here, single coefficients on the treatment variable (*Post*) are dropped because of perfect multicollinearity arising from the inclusion of country-year fixed effects. Columns II and VI use the binary treatment indicator. In Column III (VII), the patent stock (cost) variable is interacted with our continuous treatment variable. If not stated otherwise, all regressions control for the level of the firm-specific treatment variable; coefficients are not reported but statistically insignificant. Standard errors (in parentheses below coefficients) are heteroscedasticity-consistent and clustered at the firm level.

Table 6: Country- and industry-specific heterogeneous treatment effects

Panel A: Country-specific affectedness: heterogeneous degrees in the legislative change

Dependent variable:	Debt-ratio							
Portfolio value definition:	Patent costs				Patent stock			
Level of legislative changes:	High	Medium	Low	All	High	Medium	Low	All
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
Affected (A) × Post (P)	5.776	2.635	0.448		5.130	2.139	1.064	
	(1.721)	(1.288)	(1.106)		(1.697)	(1.296)	(1.117)	
(A×P) × Change^{High}				5.722				5.238
				(1.720)				(1.702)
(A×P) × Change^{Medium}				2.604				2.173
				(1.285)				(1.315)
(A×P) × Change^{Low}				0.445				1.059
				(1.115)				(1.129)
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	0.05	0.09	0.07	0.08	0.05	0.09	0.07
Observations	6,152	12,306	10,410	28,868	6,152	12,306	10,410	28,868

Panel B: Industry-specific affectedness: heterogeneity in the competitive environment

Dependent variable:	Debt-ratio							
Portfolio value definition:	Patent costs				Patent stock			
Pre-treatment competition:	High	Medium	Low	All	High	Medium	Low	All
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
Affected (A) × Post (P)	4.475	2.891	0.239		4.554	2.788	0.207	
	(1.725)	(1.162)	(1.207)		(1.657)	(1.167)	(1.239)	
(A×P) × Comp.^{High}				3.076				3.285
				(1.458)				(1.458)
(A×P) × Comp.^{Medium}				2.684				2.421
				(1.107)				(1.458)
(A×P) × Comp.^{Low}				1.926				2.130
				(1.011)				(1.458)
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	0.11	0.07	0.07	0.07	0.11	0.07	0.07	0.07
Observations	6,642	11,468	10,499	28,609	6,642	11,468	10,499	28,609

Notes: Both tables present estimates from regressions explaining the effect of the Enforcement Directive on firms' debt ratios. Regressions are equivalent to the main specification (Equation 4) and Column I in Table 5 but distinguishing among different intensities affectedness. Panel A considers heterogeneity in the country-specific degree of legislative change. Regressions are separately run for firms with high (Columns I and V), medium (Columns II and VI), and low levels (Columns III and VII) of legislative changes. The actual degrees of change refer to the individual amendments and the overall degree of change in the legal system of EU member states following the Articles of the Enforcement Directive as defined in Figure 4. Countries with high (low) degree of amendments have more (less) than seven adjustments - partial or complete - out of the eleven relevant Articles. A medium degree in adjustments refers to the country-specific median number of changes, that is, seven partial or full changes. Regressions in Columns IV and VIII use the full sample and include (triple-)interaction terms of the DID estimators with dummy variables equal to one for high (Change^{High}), medium (Change^{Medium}), and low (Change^{Low}) degree of adjustments. Panel B considers industry-specific competitive environments. Regressions are separately run for firms with high (Columns I and V), medium (Columns II and VI), and low levels (Columns III and VII) of competition. High (low) competition refers to firms in the top (lower) tercile of the pre-treatment competition distribution. Competition is approximated by calculating industry-specific pre-treatment averages of mark-ups as described in Section 4.2. Equivalent to Panel A, regressions in Columns IV and VIII use the full sample and include (triple-)interaction terms of the DID estimators with dummy variables equal to one for high (Comp.^{High}), medium (Comp.^{Medium}), and low (Comp.^{Low}) competition. In both Panels, the two measures for patent portfolio value are applied: patent costs (Columns I-IV) and patent costs (Columns V-VIII). All regressions include level variables of *Post* and portfolio value variables. Standard errors (in parentheses) are heteroscedasticity-consistent and clustered at the firm level.

Table 7: Firm-level characteristics of patenting and matched, non-patenting firms

	Patenting	**Non-patenting**	**Difference in means**
Debt-ratio (in %)	9.599	8.795	0.804
Employees (#)	199	180	19
Age	20.8	20.6	0.2
Quoted (in %)	1.566	1.620	-0.016
Firm size (log. assets)	8.083	8.044	0.039
Profitability (RoA)	0.131	0.124	0.007
Tangibility	0.125	0.125	0.000
Cash flow-ratio	0.096	0.092	0.004

Notes: The table provides the mean values of key, firm-level variables distinguishing among patenting and non-patenting firms from the matched sample. Non-patenting firms are obtained by using CEM as described in Section 4.3.1. The values reflect pre-treatment means of the two groups. Variables are used as in Table 3 but do not include patenting variables. The last column displays the differences in mean values. Note that none of the differences in means is statistically significant (t-values are not displayed).

Table 8: Treatment effect: patenting versus non-patenting firms from a matched sample

Dependent variable:	Debt-ratio				
	(I)	(II)	(III)	(IV)	(V)
Patenter × Post		1.793	1.594	1.510	1.502
		(0.848)	(0.784)	(0.774)	(0.781)
Post		0.243	0.014		
		(0.519)	(0.479)		
Patenter	0.616	0.594	2.550		
	(0.755)	(0.776)	(1.901)		
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
R^2	0.00	0.00	0.03	0.08	0.09
Observations	11,573	10,759	9,692	9,692	9,692

Notes: The table presents estimates from regressions explaining firms' debt ratios on the sample of matched firms, which contains patenting (treatment) and non-patenting (control group) firms. The indicator *Patenter* equals one (zero) if a firm belongs to the treatment (control) group. Column I includes the *Patenter* indicator. Column II further adds the binary treatment variable (as defined in Section 3.3) and its interaction with the *Patentee* variable. Column III estimates Equation (5) and further controls for capital structure determinants as defined in Table 3. Columns IV and V additionally control for a set of fixed effects as indicated at the bottom of the table. Here, the single indicator variables (i.e., *Patenter* and *Post*) are omitted from estimations because of perfect multicollinearity. Standard errors (in parentheses below coefficients) are heteroscedasticity-consistent and clustered at the firm level.

Table 9: Plausibility analysis: the announcement effect

Dependent variable:	Debt-ratio							
Time window:	Full sample				Pre-treatment			
Portfolio value definition:	Patent stock		Patent costs		Patent stock		Patent costs	
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
Affected × Post^{2004}	1.144		1.425		0.287		0.929	
	(0.590)		(0.588)		(0.585)		(0.587)	
Portfolio value × Post^{2004}		13.523		1.768		5.484		0.987
		(5.048)		(1.052)		(3.907)		(1.178)
Portfolio value	6.866	-1.072	-0.021	-0.774	-0.743	-2.816	-0.049	-0.239
	(5.097)	(5.000)	(1.079)	(1.196)	(3.709)	(4.240)	(1.076)	(1.178)
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 a *placebo* setting. Regressions are equivalent to specifications from Column I and III from Table 5 and only differ in the use of the treatment indicator. Replacing the *Post* dummy from Equation (4), $Post^{2004}$ is a dummy variable, which equals one for all years following 2004 and zero otherwise. This reflects the Announcement date of the Enforcement Directive by the European Parliament. Columns I-IV contain the full sample, while Columns V-VIII contains only the country-specific years *before* the Enforcement Directive was actually implemented. Both measures for patent portfolio value are applied: patent stock (Columns I-II and V-VI) and patent costs (Columns III-IV and VII-VIII). Standard errors (in parentheses below coefficients) are heteroscedasticity-consistent and clustered at the firm level.

Table 10: Comparing the Crisis and Enforcement Directive effects

Dependent variable:	Debt-ratio							
Portfolio 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)		
Portfolio value × Post			13.433	21.211			1.346	4.317
			(6.473)	(6.880)			(1.308)	(1.523)
Portfolio value × Crisis			6.407	3.201			0.794	-1.054
			(5.816)	(5.365)			(1.141)	(1.170)
Portfolio value	7.431	7.324	0.697	-2.240	0.383	0.072	-0.194	-0.927
	(5.023)	(5.065)	(3.720)	(3.764)	(1.095)	(1.094)	(1.039)	(1.080)
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 estimates from regressions explaining firms' debt ratios in a *placebo* setting. Regressions are equivalent to specifications from Column I and III from Table 5 but add a second treatment indicator, i.e., a *Crisis*-dummy variable interacted with either the treatment indicator (Columns I-II and V-VI) or the continuous measure of patent portfolio value (Columns III-IV and VII-VIII). *Crisis* is equal to one if the respective firm's home country is in a recession as defined in accordance with Laeven and Valencia (2013). For the treatment dummy (*Post*), we use the two specifications introduced in Section 3.3: a dummy indicating whether the enforcement directive is implemented in the home country (Columns I, III, V, and VII) and a continuous variable measuring the fraction of the firms' designated states that implemented the directive (Columns II, IV, VI, and VIII). Regressions include the level variable of the treatment variables, i.e., *Post* and *Crisis* (undisplayed). Patent stock (Columns I-IV) and patenting costs (Columns V-VIII) are used to measure portfolio values. Standard errors (in parentheses below coefficients) are heteroscedasticity-consistent and clustered at the firm level.

Table 11: Complementarity of tangible assets across firm sizes

Dependent variable:	Debt-ratio					
Sample (Tangibility)	High (>Q75)	Medium (Q25-50)	Low (<Q25)	Full sample		
Panel A: All firms						
	(I)	(II)	(III)	(IV)	(V)	(VI)
Affected × Post (A × P)	2.837	2.568	1.501	1.999	2.962	2.596
	(1.595)	(1.086)	(2.010)	(0.926)	(0.873)	(1.006)
(A × P) × Tangibility^{Q75}				1.758		1.180
				(1.586)		(1.622)
(A × P) × Tangibility^{Q25}					-2.585	-2.235
					(1.803)	(1.849)
R^2	0.11	0.08	0.07	0.07	0.07	0.07
Observations	7,475	15,208	6,124	28,807	28,807	28,807
Panel B: Small and medium-sized firms (<500 employees)						
	(I)	(II)	(III)	(IV)	(V)	(VI)
Affected × Post (A×P)	5.752	3.377	2.446	3.025	4.431	3.718
	(2.648)	(1.547)	(2.560)	(1.304)	(1.324)	(1.479)
(A×P) × Tangibility^{Q75}				3.178		2.510
				(2.735)		(2.794)
(A×P) × Tangibility^{Q25}					-2.995	-2.312
					(2.479)	(2.524)
R^2	0.15	0.10	0.07	0.08	0.08	0.08
Observations	3,974	8,572	4,133	16,679	16,679	16,679
Panel C: Large firms (≥500 employees)						
	(I)	(II)	(III)	(IV)	(V)	(VI)
Affected × Post (A×P)	-0.098	1.344	-1.370	0.422	1.040	1.037
	(1.929)	(1.532)	(3.654)	(1.326)	(1.167)	(1.381)
(A×P) × Tangibility^{Q75}				0.608		0.011
				(1.835)		(1.879)
(A×P) × Tangibility^{Q25}					-2.670	-2.667
					(2.683)	(2.765)
R^2	0.10	0.06	0.12	0.06	0.06	0.06
Observations	3,501	6,636	1,991	12,128	12,128	12,128
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: The table presents estimates from regressions explaining the effect of the Enforcement Directive on firms' debt ratios. Regressions are equivalent to the main specification (Equation 4) and Column VI in Table 5 but distinguishing among different degrees of tangibility intensities and firm size. Tangibility is defined in Panel B of Table 3 and is calculated based on firms' pre-treatment average values. Regressions are separately run for firms with high (Column I), medium (Column II), and low levels (Column III) of pre-treatment tangible assets. High (low) tangibility refers to firms in the top (lower) quartile of the pre-treatment tangibility distribution. Regressions in Columns IV-VI use the full sample and include additional (triple-)interaction terms of the DID estimators with dummy variables equal to one for high (Column IV), low (Column V), and both, high and low (VI) tangibility. Panel A uses all firms, while Panel B (C) repeats the described specifications on subsets 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. Standard errors (in parentheses) are heteroscedasticity-consistent and clustered at the firm level.

Table 12: 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	3.968	3.122			1.029	2.043		
	(1.280)	(1.189)			(1.651)	(1.549)		
Portfolio value × Post			4.663	24.015			4.071	9.187
			(2.517)	(11.616)			(3.294)	(12.556)
Portfolio value	-1.455	4.585	-2.588	-7.347	-0.359	13.715	-1.241	8.488
	(1.830)	(8.393)	(2.024)	(10.508)	(1.651)	(9.764)	(1.852)	(8.217)
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 S&A-index score							
Dependent variable:	Debt-ratio							
	Constrained				Unconstrained			
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
Affected × Post	2.147	4.179			2.141	1.428		
	(1.244	(1.294)			(1.022)	(1.057)		
Portfolio value × Post			6.614	23.675			1.303	23.962
			(2.324	(8.614)			(1.965)	(11.866)
Portfolio value	-1.240	6.367	-3.113	-4.659	0.112	7.772	0.556	-0.734
	(1.531)	(6.586)	(1.497)	(5.195)	(1.474)	(8.050)	(1.483)	(5.648)
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 the effect of the Enforcement Directive on firms' debt ratios. Regressions are equivalent to specifications from Column I and III from Table 5 but are run on split samples according to firms' pre-treatment propensity to be financially constrained. Panel A approximates financing constraints by the RZ-score as defined in Rajan and Zingales (1998). Panel B classifies constraints according to the S&A score as defined in Hadlock and Pierce (2010). Both measures are described in Section 5.1. In both panels, the sample is split 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, III, V, and VII (II, IV, VI and VIII) use the continuous (binary) treatment variable as defined in 3.3. Portfolio value refers to the cost measure as defined in Equation (2). Standard errors (in parentheses below coefficients) are heteroscedasticity-consistent and clustered at the firm level.

Table 13: Portfolio value, the Enforcement Directive, and the costs of obtaining debt

Panel A: Summary statistics on firm-level interest burden across time and firm types

Portfolio value		**Q5**	**Q25**	**Q50**	**Q75**	**Q95**	**Means**	**Difference in means** (t-values)
All firms	Pre	1.12	5.46	8.35	12.58	18.37	9.08	-0.16 (2.56)
	Post	1.25	5.08	8.25	12.29	18.39	8.92	
High (Affected= 1)	Pre	0.73	5.35	8.31	12.54	18.54	9.02	-0.28 (2.13)
	Post	1.12	4.89	8.02	12.05	18.39	8.74	
Low (Affected= 0)	Pre	1.26	5.47	8.37	12.60	18.28	9.10	-0.07 (1.58)
	Post	1.40	5.17	8.39	12.41	18.39	9.03	

Panel B: DID estimations explaining the costs of debt after the adoption of the Directive

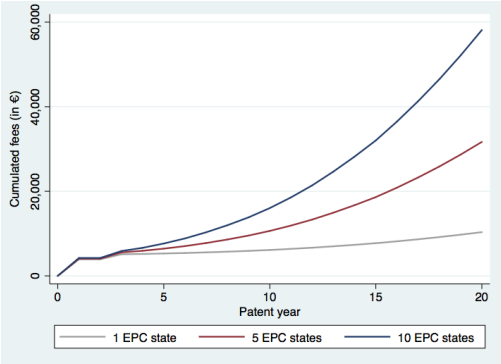
Dependent variable:	Interest burden ratio			
	(I)	(II)	(III)	(IV)
Affected × Post × Beneficiary		-1.677	-2.502	-1.728
		(0.728)	(0.994)	(0.535)
Affected × Post	-0.294	0.014	-0.086	0.322
	(0.322)	(0.340)	(0.330)	(0.381)
Portfolio value	-1.106	-1.254	-1.092	-1.268
	(1.109)	(1.110)	(1.116)	(1.134)
Firm size	0.016	0.018	0.010	0.007
	(0.154)	(0.153)	(0.154)	(0.153)
Profitability	2.536	2.545	2.540	2.508
	(0.677)	(0.675)	(0.678)	(0.676)
Tangibility	-0.726	-0.758	-0.708	-0.686
	(0.617)	(0.615)	(0.615)	(0.615)
Cash flow	-2.764	-2.749	-2.763	-2.712
	(0.758)	(0.755)	(0.759)	(0.755)
Constant	8.457	8.433	8.505	8.537
	(1.603)	(1.601)	(1.603)	(1.600)
Financial constrained measure:	-	RZ-score	S&A index	Public
Additional controls:				
Firm FE	Yes	Yes	Yes	Yes
Country-Year FE	Yes	Yes	Yes	Yes
R^2	0.06	0.06	0.06	0.06
Observations	14,688	14,688	14,688	14,688

Notes: This table illustrates different properties of firms' costs of obtaining debt. Panel A provides summary statistics on firms' interest burden. Mean values are displayed for the firm-specific pre- and post-treatment periods and regarding to firms' ex ante portfolio value. Before (after) denotes the firm specific pre- (post-) treatment period, i.e., once $Post > 0$ ($Post = 0$). Portfolio value refers to the cost measure as defined in Equation (2). The last column displays the difference between pre- and post-treatment means (t-values are displayed in parentheses below the means). Panel B presents estimates from regressions explaining firms' interest burden. The regression displayed in Column I replicates the capital structure equation estimated in Table 5 but use firms' annual interest to average debt ratios as dependent variable. In Columns II-IV, a second interaction term is added to the same specification as in Column II: we multiply the DID estimator (i.e., *Affected* × *Post*) with a dummy equal to one for firms that are considered as beneficiary from the Enforcement Directive or zero otherwise. Beneficiaries fulfill two criteria. First, they must have increased debt-ratios comparing pre- and post amendment levels and, second, they are ex ante financially constrained firms (see Section 5.1). We define financing constraints equivalent to previous estimations, namely by firms' ex ante RZ-score (Column II), S&A index (Column III), and their legal status, that is whether they are private or public firms (Column IV). Standard errors (in parentheses) are heteroscedasticity-consistent and clustered at the firm level.

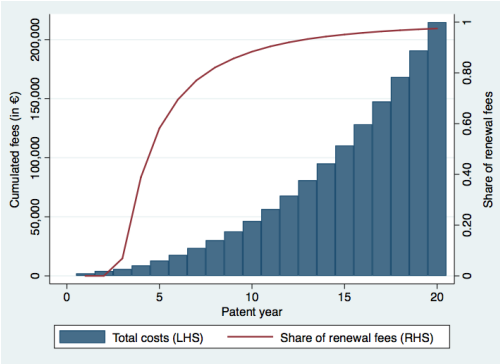
Figures from the main part:

Figure 1: Descriptive statistics: Patent costs over the patent life cycle

Panel A: Patent costs, geographical scope



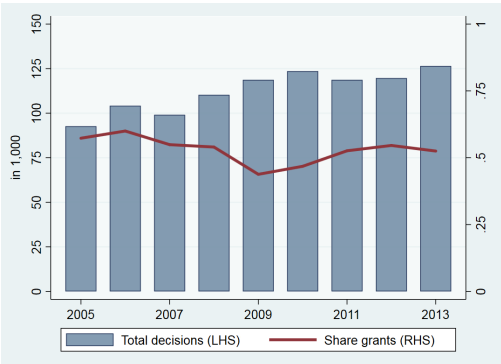
Panel B: Cumulative patent costs



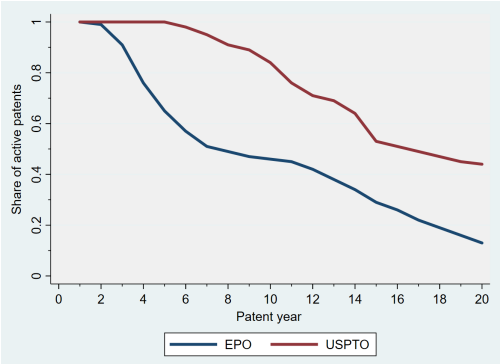
Notes: The two graphs illustrate the obligatory administrative patent fee structures for patents active in EPC member states over the patent life cycle. Panel A displays the *average* annual fees necessary to maintain patent protection for each of the maximum 20 years of patent life. These costs include the most common application, grant, and renewal fees and are subject to change over time. For illustration purposes, one reference payment schedule is selected, i.e., 2006 (see Table IA1 in the Internet Appendix A). Costs are plotted according to different numbers of designated jurisdictions where the patent is renewed: 1, 5, or 10 jurisdictions, respectively. Panel B plots the *cumulative* amount of all fees over the patent life span (blue bars, left axis) and the share of renewal costs among total patenting costs (red line, right axis). Here, values resemble costs for an *example firm* which holds 5 patents across 8 jurisdictions (compare with Table IA2 in the Internet Appendix A). The patenting fee elements comprise legal, re-occurring administrative costs and do not include irregular costs, such as court costs or attorney fees.

Figure 2: Aggregate statistics: patent grant and lapse characteristics

Panel A: Grant rates at EPO, 2005-2013

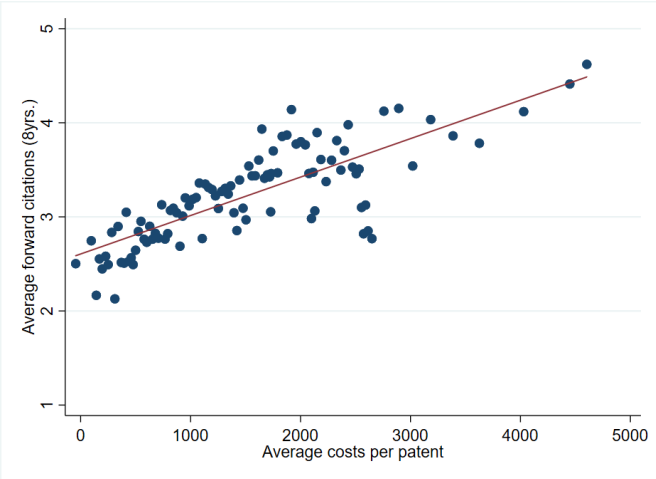


Panel B: Patent life at EPO & USPTO



Notes: These figures display (out-of-sample) aggregate statistics on patent grant and lapse characteristics. Panel A displays the total number of patent decisions and grant rates at EPO between 2005-2013; the bars resemble grant decisions on patent filings (left axis). Applications withdrawn prior to publication date at 18 months after filings are excluded. The red line plots granted patents as a fraction of total decisions (right axis). Here, applications may not be granted due to refusal by EPO as well as deliberate withdrawal prior or during examination. The graph is based on data from Harhoff (2016). Panel B compares the fraction of granted patent registrations that are still in force for each patent year starting with the year of filing, differentiating among EPO (blue) and at USPTO (red) patents. The EPO shares represent a weighted average ratio of patent renewals made for European patents in the EPC states. The reference year is 2010. Data is obtained from IP5 (2018).

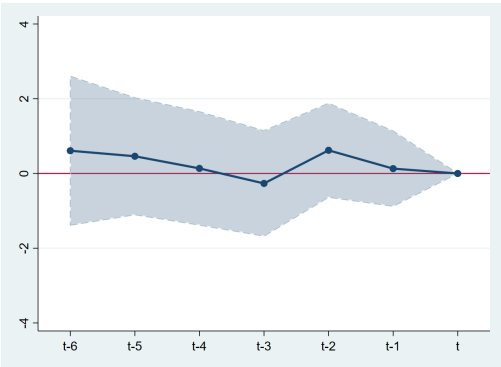
Figure 3: Relating patent citations to patenting costs



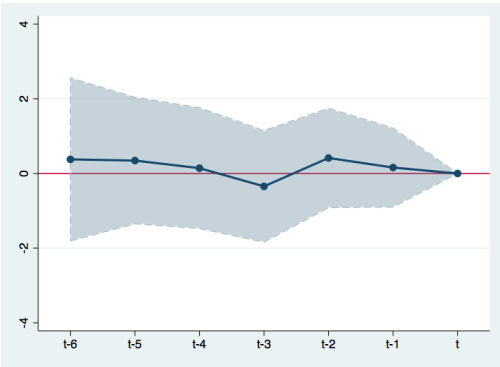
Notes: This binned scatter plot relates the average number of forward citations received by a patent within the first eight years after filing to the average costs per patent. The graph compares within portfolio averages and accounts for mechanical effects arising from age differences by controlling for the average portfolio age and the age of the firm. The number of bins is 100.

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

Panel A: Patent stock

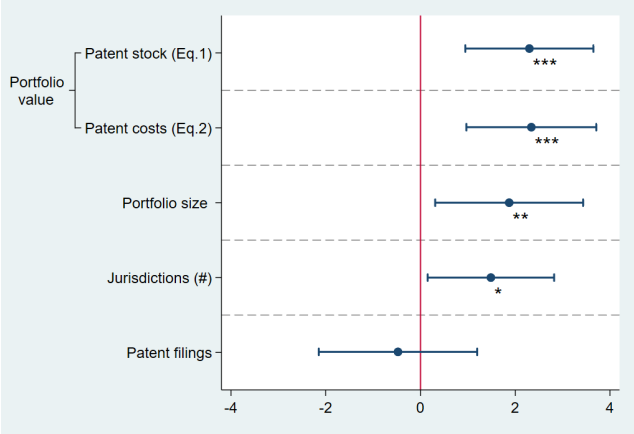


Panel B: Patent costs



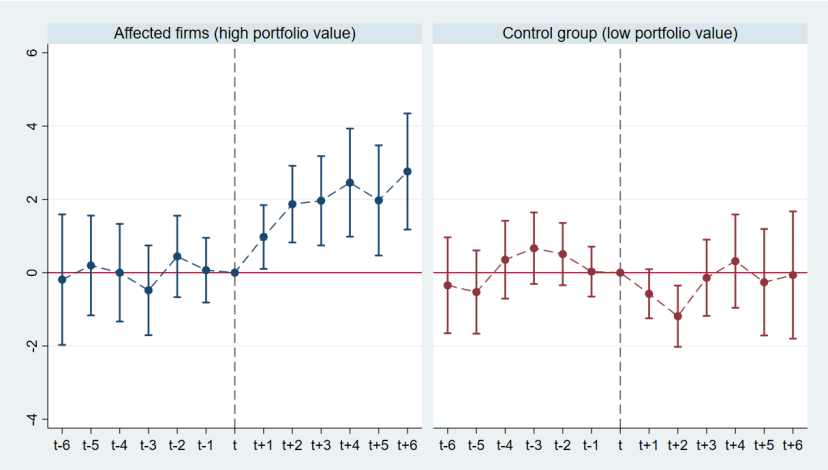
Notes: This figure plots coefficients from estimations explaining changes in firms' debt ratios during the pre-treatment period. Regressions are equivalently set up as specified in Equation (4) but include a set of interactions of year dummies with the *Affected* indicator. The underlying sample excludes all country-specific years for which $Post > 0$. Year dummies indicate the relative number of years before the implementation of the Enforcement Directive. Both regressions determine affected firms as described in Section 3.3 but use varying definitions on ex ante patent portfolio values. In Panel A, portfolio value is determined by the patent stock measure (Equation 1), whereas Panel B uses the patent costs definition (Equation 2). The implementation year, t, is the base year. The shaded area marks the 95 percent confidence intervals of the estimates.

Figure 5: 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) using different patent measures to determine firms' affectedness to the implementation of the Enforcement Directive. The first two rows use the main treatment measures indicating firms with an above median patent portfolio value prior to treatment as defined by Equations (1) and (2), respectively. The third and fourth row uses the single components of the patent stock variable: Firms are classified as treated with an ex ante above median patent portfolio size (Row 3) or number of active jurisdictions (Row 4). The last row defines a firm as treated, if it filed at least one patent in the period preceding the adoption of the Directive. Whiskers span the 90 percent confidence intervals. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Figure 6: Coefficient plot: lag structure of the treatment effect



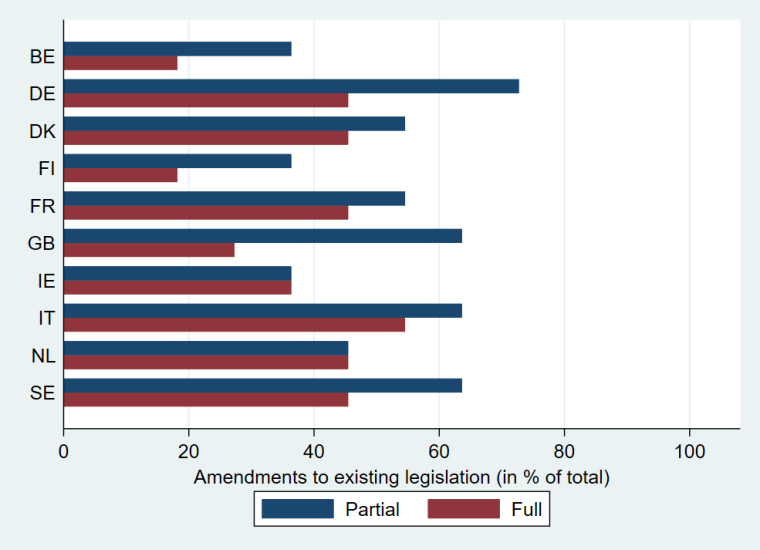
Notes: These figures plot coefficients from estimations explaining changes in firms' debt ratios in an event study design. Regressions are equivalently set up as specified in Equation (4) but include a set of interactions of year dummies with a dummy indicating firms ex ante patent portfolio value. Year dummies indicate the country-specific relative number of years before and after the implementation of the Enforcement Directive. Specifically, the plot displays the coefficients, $\alpha^{Hi}_{\tau_i}$ (left graph) and $\alpha^{Lo}_{\tau_i}$ (right graph), of the two individual regressions ($s \in [Hi, Lo]$): $Debt\ ratio_{it} = \alpha^s(Firm^s_i \times Enforcement_{t+\tau_i}) + \beta CS_{it} + \vartheta_i + \eta_{ct} + u_{it}$, 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 $s \in [Hi, Lo]$ is a dummy variable equal to one if firm i has an ex ante patent portfolio value above ($s = Hi$) or below ($s = Lo$) the median, and zero otherwise. Value refers to the patent portfolio cost measure as defined in Equation 2. The remaining variables are specified in Table 3. Whiskers span the 90 percent confidence intervals.

Figure 7: Enforcement Directive amendments implemented across EU members

Panel A: Country-amendments matrix

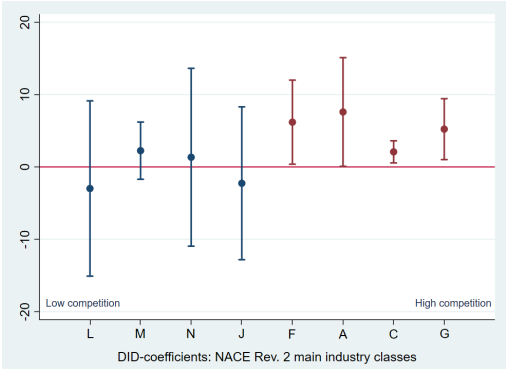
	Enforcement Directive Articles											Number of changes	
Country	4	5	6	7	8	9	10	11	13	14	15	Partial	Full
Austria	1	0	0	2	1	1	0	0	0	0	0	4	1
Belgium	1	1	0	0	2	0	0	0	0	0	2	4	2
Denmark	0	2	0	1	2	0	2	0	2	0	2	6	5
Finland	0	0	0	0	2	2	0	1	0	0	1	4	2
France	0	0	1	0	2	2	2	0	2	0	2	6	5
Germany	0	2	2	2	2	1	2	0	1	0	1	8	5
Greece	2	1	2	2	2	2	2	2	0	2	0	9	8
Ireland	0	2	0	0	2	0	2	0	0	0	2	4	4
Italy	0	2	2	2	2	2	1	2	0	0	0	7	6
Netherlands	0	0	2	2	2	0	0	0	0	2	2	5	5
Portugal	1	2	2	0	2	2	2	2	2	0	2	9	8
Spain	1	1	2	2	2	0	1	2	2	0	2	9	6
Sweden	0	0	0	1	2	2	2	2	2	0	1	7	5
United Kingdom	1	1	0	0	1	2	1	0	2	0	2	7	3
Mean												6.54	4.92
Median												7	5

Panel B: Partial and full changes of sample countries



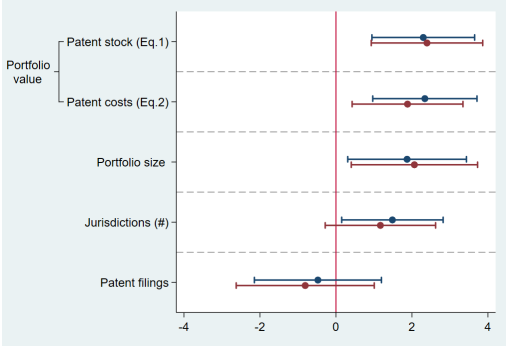
Notes: Panel A displays the individual amendments and the overall degree of change in the legal system of EU member states following the Articles of the Enforcement Directive. For this, we do not consider Articles with either an administrative or suggestive nature, Articles 1-3, 12, and 16-22, respectively. The table provides the degree of adjustment for each EU 15 country based on the remaining eleven Articles and differentiates among no changes (=0), minor adjustment or partial changes (=1), and major adjustments or new additions (=2). We hand-collect information on the implementation status from Petillion (2019). Based on this, the table indicates in the last two columns: the country-specific number of Articles that were at least partially or fully adjusted. Panel B plots the corresponding values of partial and full amendments for each EU member state in our sample as a percentage of all eleven possible changes.

Figure 8: Industry competition and heterogeneity in baseline results



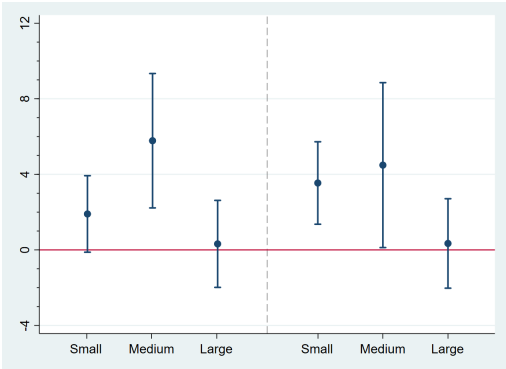
Notes: This graph plots point estimates of the difference-in-differences estimators obtained from repeating baseline regressions (Equation 4) on split samples. Regressions are separately estimated for the different NACE main categories: L (real estate activities), M (professional, scientific and technical activities), N (administrative and support service activities), J (IT and communication), F (construction), A (agriculture, forestry and fishing), C (manufacturing), and G (wholesale and retail trade). Estimates are displayed ranking industries according to their levels of competition, starting with the lowest levels. Competition is measured by country-industry-specific mark-ups, defined in Section 4.2. Firms' affectedness is determined by their ex ante patent portfolio values (Equation 1). Whiskers span the 90 percent confidence intervals.

Figure 9: Coefficient plot: DID estimators on firms surviving the financial crisis



Notes: This figure plots coefficients of the difference-in-differences estimators equivalent to Figure (5). The only difference is that regressions are run separately for all firms (blue) and those that are assumed to have survived the Financial Crisis (red). *Survivors* are defined as firms that appear at least five times in the dataset in the years after the onset of the Financial Crisis, i.e., between 2007-2012. Whiskers span the 90 percent confidence intervals.

Figure 10: DID estimators on firm size categories



Notes: This figure plots coefficients of the DID estimators obtained from the regression specified by Equation (4). Regressions are separately estimated for different firm size categories according to the average number of employees during the pre-treatment period between 2000 and 2004: small firms with less than 100 employees, medium-sized firms with 100-500 employees, and large firms with at least 500 employees, respectively. All specifications use the interaction of treatment with the binary indicator of whether firm have high ex ante patent costs. The graphs differ in the definition of the treatment variable: the left (right) graph uses the binary (continuous) treatment variable as defined in Section 3.3. To control for industry-specific borrowing costs all regressions control for industry-year fixed effects. Whiskers span the 90 percent confidence intervals.

FOR ONLINE PUBLICATION

Internet Appendix A: Tables (IA1 - IA18)

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 fee across EPC member states stipulated in the EPO payment schedule as of December 31st, 2006. The payment schedule illustrates the different fees both across jurisdictions and across patent life. Countries marked with * were no EPC member states in 2006. Originally, fees are denoted in the national currency but converted to Euro values using the official exchange rate (see Deutsche Bundesbank 2020) for countries which did not have the Euro as official currency in 2006. For San Marino and North Macedonia 2011 values are used because of data availability. For Italy, 2009 values are used, because the country temporarily expelled renewal fees between Jan. 1, 2006 and Jan. 1, 2007. 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: This panel is the continuation of Table IA1 (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 jurisdiction (in €)
1	Application fees*	2,082	2,082	-
2	Application fees*	2,082	4,164	-
3	Grant & 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 exemplifies the evolution of patenting costs of an average sample firm across time. Costs are calculated based on the EPO payment schedule as of 2006 (see Table IA1 in the Internet Appendix A). For illustration purposes, one simplifying assumption is made: Firms are assumed to make an international filing at EPO and then move respective patents to the national phase after grant, i.e., on average in the fourth year after application. Hence, these firms pay renewal fees at EPO during the third year, while moving to the national phase and thus paying fees to individual national offices beginning with year four. The costs which arise during the pre-grant period are application and grant costs. Thereby, application costs comprise examination fees, translation fees, international search fees, and filing fees. Grant costs comprise the grant and designation fees. The table displays both annual and cumulated costs as well as the average cost to renew *one* patent at *one* EPC jurisdiction. Average patent renewal expenses for the years 4 to 6 are 298 Euro, which 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.

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 sample observations 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 sample observations 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
17-22	Further duties	Sets out details on the implementation time line and progress reporting

Notes: This table summarizes the main 22 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, i.e., the so-called Enforcement Directive.

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 Enforcement Directive across EU member states. The intended deadline for implementation was April 29th, 2006. Respective dates are hand-collected from Petillion (2019). Sample countries are highlighted in bold letters. The third column displays the fraction of patents that are designated to respective jurisdictions.

Table IA7: Capital structure determinants: Firms with high and low portfolio values

Panel A: Capital structure means for affected and control groups

	Affected *(portfolio values)*		**Difference in means**		
	High	Low	Absolute	in %	(t-values)
Firm size (log. assets)	10.434	9.600	0.834	8.7	(25.06)
Profitability (RoA)	0.084	0.089	-0.005	-5.0	(1.70)
Tangibility	0.215	0.227	-0.012	-5.2	(5.11)
Cash flow-ratio	0.071	0.072	-0.002	-0.2	(0.62)
Patent stock	139.4	14.2	125.2	881.7	(31.83)
Patent costs	45,914	3,974	41,940	1,055.4	(33.19)

Panel B: Capital structure determinants before and after the legal change

	Affected	***Before***	***After***	**Difference in means**	(t-values)
Firm size (log. assets)	High (= 1)	10.199	10.831	0.632	(10.365)
	Low (= 0)	9.460	10.105	0.645	(14.723)
Profitability (RoA)	High (= 1)	0.083	0.085	0.002	(0.399)
	Low (= 0)	0.088	0.091	0.003	(0.728)
Tangibility	High (= 1)	0.221	0.204	-0.017	(4.237)
	Low (= 0)	0.230	0.218	-0.011	(3.242)
Cash flow ratio	High (= 1)	0.068	0.074	0.006	(1.769)
	Low (= 0)	0.071	0.074	0.004	(1.488)

Notes: The table compares mean values for key variables distinguishing among firms with respect to their ex ante patent portfolio values. Firms above the median value in the year before the treatment occurs are classified as affected. Panel A compares in the first two columns mean values for the capital structure determinants as described in Table 3 (Panel B), distinguishing among firms with high and low ex ante patent portfolio values. The third and fourth columns display the absolute and relative differences in mean values, respectively. The last column displays the t-values of the absolute differences in means between firms with high and low ex ante portfolio values, i.e., Column I and II, respectively. Panel B compares the average values of these capital structure determinants before and after treatment equivalent to Panel A of this table. In both panels, patent value is specified as defined in Equation (1). Using the alternative value specification from Equation (2) provides an equivalent pattern.

Table IA8: Assessment of anticipatory effects (pre-treatment)

Dependent variable:	Debt-ratio				
Treatment definition	Patent stock	Patent costs	Portfolio size	Jurisdictions (#)	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 displays coefficients from estimations explaining changes in firms' debt ratios during the pre-treatment period. Regressions are equivalently set up as specified in Equation (4). Following Figure 4, regressions include a set of interactions of year dummies, denoted as $t-j\,(\forall\, j \in [1,6])$, with the *Affected* indicator. The underlying sample excludes all country-specific years for which $Post > 0$. Hence, the reference time frame is the last period during which $Post = 0$, i.e., the firm-specific year in which the treatment occurs. Columns I and II use the main treatment measures indicating firms with an above median patent portfolio value prior to treatment as defined by Equations (1) and (2). Columns III and IV use the single components of the patent stock variable: Firms are classified as treated with an ex ante above median patent portfolio size or number of active jurisdictions. Column V defines a firm as treated, if it filed at least one patent in the period preceding the adoption of the Directive. Standard errors (in parentheses below coefficients) are heteroscedasticity-consistent and clustered at the firm level.

Table IA9: 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)		-0.158			
		(0.182)			
$T\times$ Affected (patent costs)			-0.135		
			(0.181)		
$T\times$ Affected (portfolio 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 deviating pre-trends among treatment and control group firms. Following Angrist and Pischke (2008), the sample contains only observations from the pre-treatment periods. Regressions are equivalently set up as specified in Equation (4) but include a time trend variable, i.e., a running number for each year, instead of the portfolio value variables. In Columns II and III the trend variable measure is interacted with an indicator variable equal to one if the firm has an above median portfolio value as defined according to the patent stock (Equation 1) and patent costs (2). Portfolio size and patent filings are used as alternative definitions of patenting in Columns IV and V, using. Standard errors (in parentheses below coefficients) are heteroscedasticity-consistent and clustered at the firm level.

Table IA10: Baseline regression using alternative definitions of key variables

Panel A: Alternative specifications of the dependent variable

Dependent variables:	Alternative debt proxies					
Variable definitions:	Log. debt		Total debt ratio		Loan-liability ratio	
	(I)	(II)	(III)	(IV)	(V)	(VI)
Affected × Post	0.163		1.532		0.021	
	(0.082)		(0.804)		(0.010)	
Portfolio value × Post		0.256		3.615		0.032
		(0.132)		(1.332)		0.016)
Portfolio value	0.027	-0.050	0.068	-0.805	0.000	-0.010
	(0.124)	(0.123)	(1.041)	(1.051)	(0.014)	(0.013)
R^2	0.16	0.16	0.10	0.10	0.09	0.09
Observations	21,925	21,925	32,142	32,142	25,735	25,735

Panel B: Alternative specifications of the *Affected* variable

Dependent variables:	Debt-ratio					
Ex ante value specification:	High costs	Large portfolio	Cost	Filings (pre-treat.)	Filings (count)	Filings ($t-1$)
	(I)	(II)	(III)	(IV)	(V)	(VI)
Affected × Post	2.391	1.995	1.391	1.373	0.150	-0.207
	(0.831)	(0.942)	(0.824)	(0.828)	(0.099)	1.008)
Portfolio value	0.153	0.157	0.301	0.302	0.034	0.173
	(1.094)	(1.095)	(1.107)	(1.108)	(1.097)	(1.071)
R^2	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

Panel C: Alternative specifications of the *Portfolio value* variable

Dependent variables:	Debt-ratio					
Portfolio value specification:	Sum of costs (abs.)	Cost-asset ratio	Log. costs	Portfolio size	Jurisdic. (#)	Patent filings
	(I)	(II)	(III)	(IV)	(V)	(VI)
Portfolio value × Post	0.028	0.012	0.115	0.097	0.009	0.416
	(0.012)	(0.003)	(0.075)	(0.041)	(0.004)	0.426)
Portfolio value	-0.017	-0.000	-0.005	-0.042	-0.003	-0.016
	(0.013)	(0.002)	(0.046)	(0.048)	(0.004)	(0.119)
R^2	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
Additional controls (in all regressions):						
Firm-level	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table presents estimates regressions repeating the baseline estimations but altering specifications on key variables. Panel A uses different definition on the dependent variable and repeats regressions corresponding to Columns I and III of Table 5. Debt is defined by its logarithm (Columns I and II), by the total debt-ratio (Columns III and IV), and the loan-to-liability ratio (Columns V and VI). Panel B repeats the main specification (Column I of Table 5) but uses different specifications of patenting values to determine whether the treatment indicator (*Affected*) is equal to one or zero: above median (non-normalized) patent costs (Column I), above median patent stock size (Column II), indicator for any costs (Column III), indicator for any filings during the pre-treatment period (Column IV), the number of filings during pre-treatment (Column V), and the number of filings just prior to the adoption of the Enforcement Directive (Column VI). In Panel A and B, all patenting values refer to pre-treatment values. Panel C repeats the alternative specification of the main regressions (Column III of Table 5), i.e., a continuous treatment variable, using different specifications of patenting values: the (non-normalized) sum of portfolio costs (Column I), the portfolio costs-to-asset ratio (Column II), the logarithm of costs (Column III), the number of patents within a portfolio (Column IV), the number of designated jurisdictions (Column V), and the number of patent filings (Column VI). Standard errors (in parentheses below coefficients) are heteroscedasticity-consistent and clustered at the firm level. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table IA11: Lag structure of the regression estimates (post-treatment)

Dependent variable:	Debt-ratio				
Treatment definition	Patent stock	Patent costs	Portfolio size	Jurisdictions (#)	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 displays coefficients from estimations explaining changes in firms' debt ratios during the treatment period. Regressions are equivalently set up as specified in Equation (4) but include a set of interactions of year dummies, denoted as $t+j\,(\forall\, j \in [1,6])$, with the *Affected* indicator. The sample contains a symmetric time window which includes observations spanning from the six years before to the six years after the treatment. The reference period are all years in which $Post = 0$. All remaining specifications are equivalent to those in Table IA7 (Internet Appendix A).

Table IA12: The Financial Crisis as alternative mechanism

Dependent variable:	Debt-ratio							
Sample time frame:	Full sample				Excluding post-crisis years			
Portfolio value definition:	Patent stock		Patent costs		Patent stock		Patent 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)	
Portfolio value × Crisis		9.562		1.794		21.717		1.098
		(3.665)		(0.885)		(10.215)		(1.841)
Portfolio value	7.123	4.212	0.222	-0.185	4.819	2.008	0.225	0.123
	(5.118)	(4.988)	(1.085)	(1.067)	(4.663)	(3.462)	(1.108)	(1.059)
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 in a *placebo* setting. Regressions are equivalent to specifications from Column I and III from Table 5 but use an alternative treatment indicator, i.e., a *Crisis*-dummy variable. *Crisis* is equal to one if the respective firms' home country is in a recession as defined in accordance with Laeven and Valencia (2013). Regressions are based either on the full sample (Columns I-IV) or a sample that is capped by the country-specific years after respective economies move out of the recession (Columns V-VIII). Patent stock (Columns I-II and V-VI) and patenting costs (Columns III-IV and VII-VIII) are used to measure patent portfolio values. 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.

Table IA13: DID estimations on the additional effect of firm size

Dependent variable:	Debt-ratio			
Portfolio value definition:	Patent stock		Patent costs	
Firm size measure :	Binary	Continuous	Binary	Continuous
	(I)	(II)	(III)	(IV)
Panel A: Continuous treatment variable				
Affected × Post	2.146	2.275	2.070	2.221
	(0.809)	(0.833)	(0.849)	(0.864)
Firm size × Post	1.028	0.040	0.982	0.041
	(0.648)	(0.059)	(0.833)	(0.060)
Portfolio value	6.958	6.958	7.168	7.264
	(5.036)	(5.070)	(5.043)	(5.076)
	(I)	(II)	(III)	(IV)
Panel B: Binary treatment variable				
Affected × Post	2.621	2.464	1.706	1.562
	(0.716)	(0.719)	(0.744)	(0.748)
Firm size × Post	1.001	0.298	0.953	0.317
	(0.768)	(0.135)	(0.833)	(0.060)
Portfolio value	7.418	7.265	7.446	7.276
	(5.036)	(5.070)	(5.043)	(5.076)
Additional controls (in all regressions):				
Firm-level	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
Country-Year FE	Yes	Yes	Yes	Yes
R^2	0.07	0.07	0.07	0.07
Observations	28,827	28,827	28,827	28,827

Notes: The table presents estimates explaining the effect of the Enforcement Directive on firms' debt ratio testing for the additional effects of firm size. Regressions are equivalent to specifications from Column I and III from Table 5 but additionally include an interaction term of firm size with the treatment variable. Because size parameters are analyzed, size control variables are excluded, which are part of the capital structure controls (see Table 3). The two panels only differ in their use of the treatment specifications: Panel A (B) uses the continuous (binary) measure as specified in Section 3.3. The binary firm size variable is an indicator equal to one (zero) for firms with above (below) median pre-treatment assets. The continuous (and time-invariant) firm size measure equals the average pre-treatment logarithm of assets. Both portfolio value measures are applied: patent stock (Columns I and II) and patent costs (Columns III and IV) as defined in Equations 1 and 2, respectively. Statistics at the bottom of the table apply for both panels. Standard errors (in parentheses below coefficients) are heteroscedasticity-consistent and clustered at the firm level.

Table IA14: Firm-level heterogeneity: private versus publicly listed firms

Dependent variable:	Debt-ratio							
Firm-type:	Private				Publicly listed			
Portfolio value definition:	Patent stock		Patent costs		Patent stock		Patent 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)	
Portfolio value × Post		26.872		3.929		-4.118		1.804
		(7.560)		(1.604)		(6.151)		(2.635)
Portfolio value	8.892	-2.555	0.336	-0.729	-5.537	-4.742	-1.987	-2.567
	(5.576)	(4.140)	(1.181)	(1.229)	(5.035)	(6.014)	(1.931)	(2.049)
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. Regressions are equivalent to specifications from Column I and III from Table 5 but are run separately on two subsamples. Columns I-IV repeat the baseline estimations for a subsample of firms that are privately owned. Columns V-VIII use a subsample of firms listed on the stock market. Both portfolio value measures are applied: patent stock (Columns I-II and V-VI) and patent costs (Columns III-IV and VII-VIII) as defined in Equations 1 and 2. Standard errors (in parentheses below coefficients) are heteroscedasticity-consistent and clustered at the firm level.

Table IA15: 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 exemplifies the fragmentation of intellectual property rights enforcement in the European Union before the implementation of the Enforcement Directive in the mid-2000s. Specifically, different rule on the application of injunctions that were in place across EU member states are listed. The reference year of these rules is 2003, i.e., one year prior to the intended implementation date of the Enforcement Directive. Information are gathered from European Commission COM(2003) 46. For the sake of illustration, the rules are summarized and focus on a subset of member states which are representative for the data sample using in the empirical analysis of this paper.

Table IA16: Patenting and debt use across industries: tech versus non-tech firms

Panel A: Descriptive statistics on patent characteristics

	Mean values			
Industries:	**Tech firms**	**Non-tech firms**	**Difference in means**	**(in %)**
Patents filed (p.a.)	0.51	0.31	0.20	(64.45)
Large portfolio	0.14	0.09	0.05	(55.56)
Active patents	5.76	3.91	1.85	(47.31)
Active jurisdictions (avg.)	7.89	7.44	0.45	(6.04)
Patent age (avg.)	6.98	7.04	-0.16	(-0.85)
Patent stock	38.18	36.59	1.59	(4.35)
Patent costs	12,969	9,122	3,846	(41.95)
Patenting costs (per patent)	1,025	1,041	16	(-1.54)
Debt-ratio	13.82	16.67	-2.85	(-17.10)
RZ index	0.24	0.38	-0.14	(-36.84)

Panel B: Definition on high-, medium-, and low-tech industries

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; wood textile, wearing apparel, leather and 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: Panel A compares mean values of patent characteristics distinguishing among firms belonging to tech-oriented or non-tech sectors as classified by Eurostat (2018). All patent-related variables equivalent to those specified in Panel A of Table 3. Further, mean values of the portfolio value measures are included. In addition to this, two financial variables are included, namely the RZ index (as defined in Section 5.1) and firms' debt ratios. The last two columns display the absolute and relative differences in mean values between tech- and non-tech firms, respectively. Panel B table displays the sectoral classification as proposed by Eurostat (2018). The table lists the different tech-orientations, the corresponding NACE Rev. 2 categories (2-digit level), and a verbal description of respective sectors. This aggregation of manufacturing industries relies on each industries level of technological intensity, i.e., R&D expenditure as a share of value added.

Table IA17: Industry-level heterogeneity: tech versus non-tech firms

Dependent variable:	Debt-ratio							
Sectoral affiliation:	Tech sectors				Non-tech sectors			
Portfolio value definition:	Patent stock		Patent costs		Patent stock		Patent 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)	
Portfolio value × Post		34.186		4.551		11.607		2.045
		(10.307)		(1.927)		(7.786)		(2.129)
Portfolio value	12.700	-3.560	-0.825	-2.185	3.481	-0.846	1.046	0.593
	(11.124)	(7.899)	(1.662)	(1.624)	(3.253)	(3.331)	(1.515)	(1.634)
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 regressions explaining firms' debt ratios. Regressions are equivalent to specifications from Column I and III from Table 5 but are run separately on two subsamples. Columns I-IV repeat the baseline estimations for a subsample of firms from tech sectors. Columns V-VIII use a subsample of firms from non-tech sectors. Sectors are defined in accordance to Eurostat (2018). Both portfolio value measures are applied: patent stock (Columns I-II and V-VI) and patent costs (Columns III-IV and VII-VIII) as defined in Equations 1 and 2. Standard errors (in parentheses below coefficients) are heteroscedasticity-consistent and clustered at the firm level.

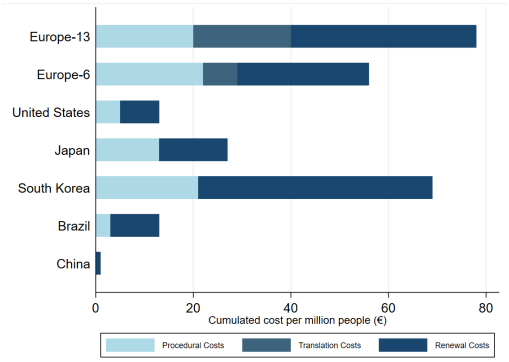
Table IA18: Patent-level heterogeneity: broad versus specific patent portfolios

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		2.443					
	(1.766)		(1.209)					
Portfolio value× Post		19.090		25.369	14.802	27.490	43.775	1.884
		(18.794)		(8.838)	(16.044)	(11.017)	(12.683)	(8.800)
Portfolio value	11.588	-0.233	7.867	-0.205	3.879	-8.844	3.687	11.679
	(7.039)	(10.090)	(6.456)	(4.469)	(9.960)	(5.947)	(4.331)	(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 regressions explaining firms' debt ratios. Regressions are equivalent to specifications from Column I and III from Table 5 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 (Columns III-IV) if they refer to more than one technology class. In Columns V-VIII, the sample of firms with a broad pre-treatment portfolio is split 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. Standard errors (in parentheses below coefficients) are heteroscedasticity-consistent and clustered at the firm level.

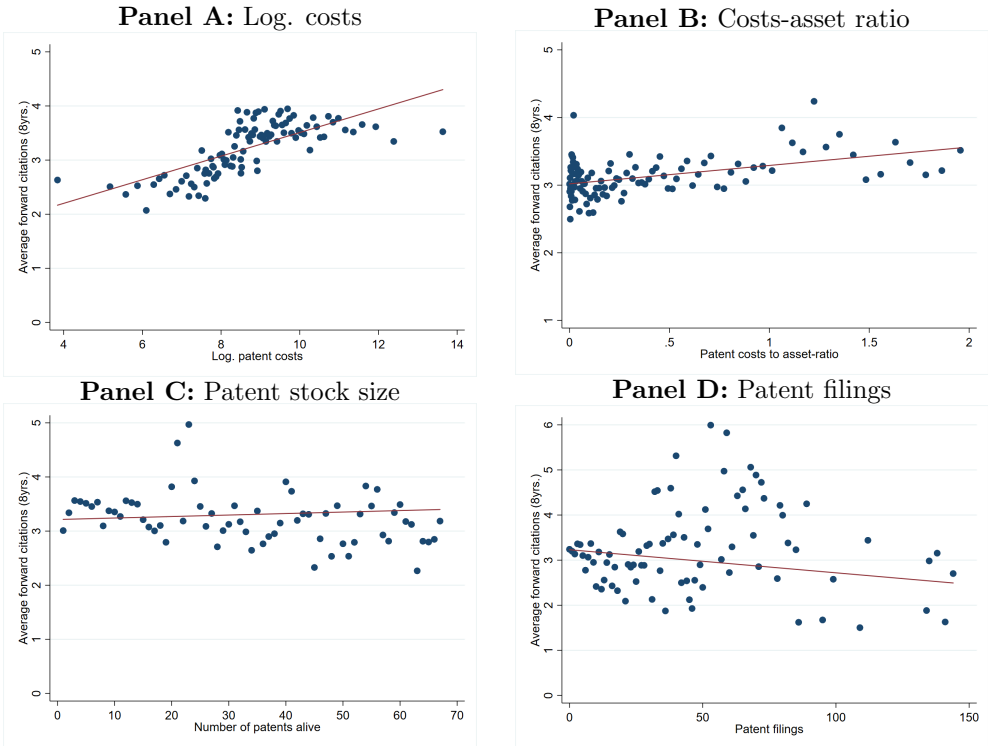
Internet Appendix B: Figures (IA1 - IA6)

Figure IA1: Patenting costs: an international comparison of fees



Notes: This graph plots the cumulated costs for six major patenting jurisdictions across the world. Costs are normalized by respective jurisdictions' sizes (per million inhabitants) and 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 patents active in 13 (6) EPC jurisdictions. Own illustration based on de la Potterie (2010).

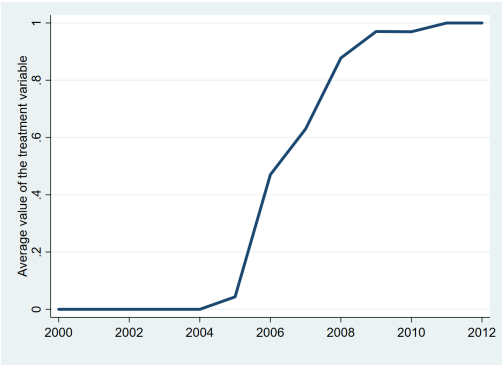
Figure IA2: Relating patent citations to (cost-related) patenting measures



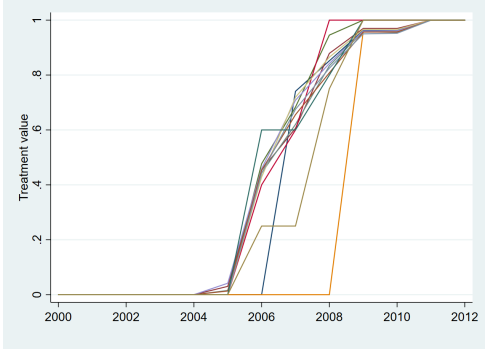
Notes: These binned scatter plots relate the average number of forward citations received by a patent in a firm's patent portfolio (within the first eight years after filing) to several patenting measures. The first two panels use variants of our patent cost measure as defined in Equation (2): the logarithm of total patenting expenditures (Panel A), the total annual patenting costs to asset ratios (Panel B). Panel C and D use more common patent metrics, i.e., the size of the patent portfolio and the number of patent filings, respectively. The number of bins is set to 100 in all four graphs.

Figure IA3: Evolvement of the continuous treatment variable over time

Panel A: Average value of treatment

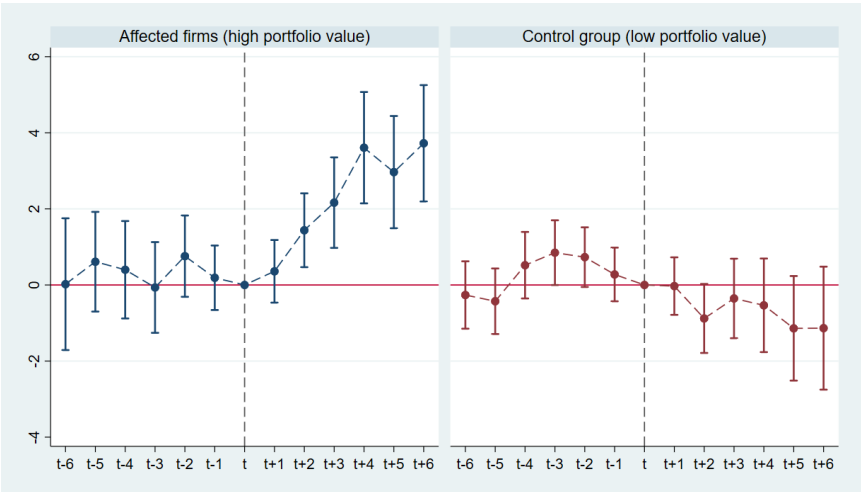


Panel B: Firm-specific values of treatment



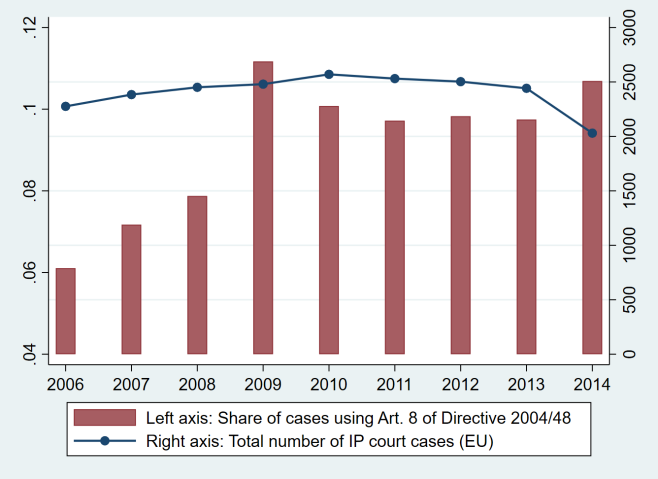
Notes: This figures plot the value of the treatment variable across the sample time window. Here, treatment refers to the relative share of all relevant jurisdictions of a sample firm which implemented the Enforcement Directive. For any firm, jurisdictions are relevant if at least one patent out of their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

Figure IA4: Lag structure of the treatment effect using *patent stock* as value measure



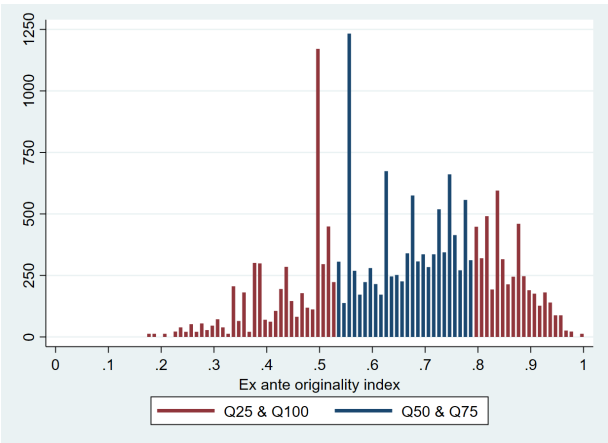
Notes: This figure depicts the development of treatment and control groups of patent portfolios on firms' leverage before and after the treatment analogue to Figure 6. Only here the treated dummy indicating whether the firm is considered as an ex ante high patenting firm is defined by median split according to the pre-treatment patent stock measure as specified by Equation (1). All other specifications remain the same.

Figure IA5: 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).

Figure IA6: 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.

Appendix C:
How patenting supports external debt financing

I. Theoretical considerations and propositions

Firms may benefit from their patent portfolio to attract external debt financing in two ways. First, firms may directly include patents in loan contracts by explicitly pledging them as collateral. Debt is thus secured by specific assets, whose liquidation value is the key determinant of creditors' payoffs in bankruptcy. Mann (2018) shows that firms directly pledge patents as collateral allowing them to increase their debt capacity. Alternatively, firms can utilize their patent portfolio to attract debt financing in a more subtle way. Patents are important signals on firms' future performance (e.g., Spence 2002) and thus particularly informative for investors. More specifically, 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 Žaldokas (2021) 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. Because of the repeated decision of incurring the costs of annual renewals, valuable patents are maintained, on average, for a longer time span (de Rassenfosse and Jaffe 2018). Following these considerations, patenting should explicitly and implicitly support external debt financing either by acting as collateral or by signaling future cash flows, or both.

Specifying the relevant patenting dimensions is necessary to test the potential of patents to lift firms' borrowing activities appropriately. 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 Panel A Figure 2). Furthermore, only one out of five granted patents is active until reaching the maximum protection of 20 years (IP5 2018). Approximating firms' patenting activity by (granted) filings thus overestimates the actual number of patents a firm possesses, particularly several years after the initial application. Intuitively, filing a successful patent is a necessary but not sufficient condition to alter firms' debt capacity effectively. Only actively held patents should be a meaningful determinant for firm leverage. Hence, we suggest that *the number of actively held patents* (i.e., firms' patent portfolios) reduces agency costs

in the borrowing process and thereby leads to higher debt to asset ratios of firms in equilibrium.

The potential of attracting external debt is likely to vary depending on the properties of the patent portfolio itself. For example, according to Haeussler *et al.* (2014), the commercial value of firms' patents is most important from an investor perspective. Hence, patent portfolios at the lower end of the value distribution are less likely to meet demand in the market as compared to more valuable portfolios. In this context, 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 illustrates how European law provides the legal basis for the use of patents as a means 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. 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, the law of the country where rights are registered regulates formal intellectual property rights. In Europe, several country-specific rules therefore determine the use of patents.[18] Still, one can summarize generally applicable aspects on whether and how patents can be used as collateral in loan contracts. Patents qualify to serve as a means of collateralization in a debt contract through assignment by way of i) factual securitization or ii) 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, the transfer merely demands a documented mutual consent of the parties involved in order to become effective (Mes 2015). In case of none perfor-

[18] 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 the 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). 4) in Germany, patent transfers are governed by Article 15(1) Sentence 2 of the PatG.

mance 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. By nature, lending institutions are often not capable to use 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 transfer the right of use to the creditor but preserves it exclusively in the sphere of the pledging party. Similar to the factual transfer, only a documented mutual consent is required for a pledge to become effective from a contractual perspective.

Appendix D :
On the effects of the Enforcement Directive

To gain a better understanding on the effects of the Enforcement Directive, it is useful to consider the institutional setting prior to the legislative change first. Until the early 2000s, a lack of IP right enforcement lead to substantial damages in the EU: firms lost between 400-800 million Euro in the internal market due to counterfeiting and piracy during the late 1990s (EC 2000). One of the main reasons for this was the highly fragmented legal framework, which caused significant disparities in the level of protection across EU member states. 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. In addition to this, legislation only provided for enforcement measures on an optional basis, which resulted in misaligned rules for calculating damages or applying provisional measures and sanctions. Table IA15 (Internet Appendix A) exemplifies the fragmentation of IP right enforcement by comparing different national rules regarding the application of injunctions. These disparities were particularly prevalent in the case of patents, since a European patent is subject to multiple national rules for assessing infringement.

Following this, the prime goal of the Enforcement Directive was to approximate the EU's legislative systems for IP rights. The basic idea was to align all measures, procedures, and remedies available for right holders to defend their IP right in line with best practice. Several measures were particularly relevant for patent protection, such as the procurement of evidence (stipulated in Articles 6 and 7) or the right of information (Art. 8). The underlying notion was that only a homogeneous set of rules (a 'level playing field') was expected to induce reliability to the IP system, ensuring its owners to appropriate returns from their protected inventions. Likewise, a more credible system should increase lenders' willingness to acknowledge IP rights as reliable signal for providing a loan.

This notion is supported by several empirical observations. For example, an evaluation study by the European Union (2017) reveals that the introduction of the Enforcement Directive lead to a substantial decrease in the duration of patent-related court cases. This resembles an increase in efficiency of the patent enforcement system. Further, the study shows that benefits arising from the change in law were particularly large for patent holders. In a survey, 86% of respondents stated that the existing rules provided by the Enforcement Directive helped effectively to protect their IP and to prevent

IP right infringements.

Considering a specific amendment from the Enforcement Directive helps to illustrate the effect of the change in law in more detail. Before the implementation of the Directive, privacy rights prohibited judicial authorities to collect information on the origin and distribution networks of goods. Article 8, the right of information, changed this by allowing authorities to demand information that is crucial for detecting IP right infringements. In particular, the Article provides that even if an infringement has not yet been proven by a court, the claimant can request the court to issue a right of information. The rule was applied across all member states and indeed marked new legislative provisions for virtually all EU members (see also Figure 4). In a broad assessment, practicing IP lawyers from the various EU countries uniformly confirmed that the Article indeed brought a substantial change compared to prior rules (see Petillion 2019). The Article is found to address IP infringements effectively by balancing the right of information and the protection of personal data. Importantly, Figure IA5 (Internet Appendix B) displays the actual application of Article 8. Between 2006 and 2014, about 10% of all IP court cases in the EU applied this rule. Its use increased sharply after the adoption of the Enforcement Directive from 6% in 2006 to almost 12% in 2009. These numbers suggest that the Enforcement Directive did not only entail important legislative changes but also ascertains its actual application.

Appendix E:
Further heterogeneous treatment effects

The following explores several additional features that potentially cause heterogeneous effects arising from the implementation of the Enforcement Directive. Estimates from Section 4.3 suggest that the effects of patenting on firms debt capacity depend on factors that lie outside the scope of patent portfolio value. Testing specific characteristics is important for two reasons. First, it serves as plausibility analysis for the main findings. Second, exploring the full depth of the dataset provides valuable insights on the determinants of the relationship between patenting and firms' ability to attract debt.

I. Industry characteristics: tech versus non-tech firms

As a first extension, we propose that the potential to use patent portfolios to attract debt relates positively to the industry-specific propensity to patent. More specifically, firms should be better able to attract debt with their patent portfolio if patenting is a rather common practice among their peers. The idea is that patents may convey credible but noisy signals about the patent holder's future performance. The degree of ambiguity in patent signals should be lower once patenting is a more common business practice, as this enhances comparability across firms. This assumption is based on literature that finds a positive relationship between the reliability of information on firms' ability to deploy intangible assets in loan contracts (Loumioti 2012).

According to the European Patent Convention (EPC 1973, Art. 52(1)), one of the four basic requirements for the patentability of an invention is a *technical character*. This suggests that manufacturing sectors can be expected to have an obvious tendency to patent because of the technical nature of their products. To test this, Panel A of Table IA16 (Internet Appendix A) illustrates differences in patenting and financing activities between tech-oriented and non-tech firms, i.e., manufacturing and non-manufacturing firms as defined in Panel B. Statistics show that firms in tech-oriented industries 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-oriented firms appear more restricted in their access to external funding, expressed by lower debt-ratios and RZ-scores.

Combining these insights suggests that the effects of the Enforcement Directive should be more pronounced for manufacturing firms. We investigate this by splitting the sample according to whether firms belong to a tech sector or not. Results are displayed in Columns I-IV and Columns V-VIII of Table IA17, respectively. For tech firms, the coefficients of interest are large and significant across specifications. In contrast, for non-tech firms results are not as consistent. Most estimates are substantially smaller or lack significance.[19] These findings confirm that the positive effect of patenting on firms' debt capacity applies disproportionally to firms located in industries with high propensities to patenting.

II. Patent characteristics: specific versus broad patents

We further analyze whether underlying characteristics of firms' patent portfolios have an impact on firms' ability to secure loan contracts with patents. While the main analyses focus on difference in the commercial value of patent portfolios, patent characteristics also vary along other dimensions that may be important for attracting debt. For example, redeployability of assets is crucial for its use as collateral. Similarly, the ability to redeploy a patent should enhance its potential as collateral. Consistent with this, 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 proxy patent portfolios' redeployability, we follow Gambardella *et al.* (2007), who argue that patents' technological scope directly relates to revenue inflows as it affects the number of potential (subsequent) users. We use the number of technology classes a patent portfolio relates to, the so-called technological scope, as a measure of redeployability. 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 and vice versa. A priori, however, it is not clear whether a broader scope has a positive or negative effect on patent redeployability. While some scholars argue that broader patents relate to higher anticipated liquidation value (e.g., Gambardella *et al.* 2007) others do not find an effect of patent-specific characteristics, such as the patent scope (e.g., Fischer and Ringler 2014). Given the potentially important role of technological breadth, we try to

[19] 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 Table IA8 (Internet Appendix A).

answer this theoretical ambiguity in our empirical analysis.

We quantify the breadth of firms' patent portfolios by the originality index (see Hall *et al.* 2001), which captures the technological range to which patents relate. 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. Based on this, we define patent portfolios referring to one single technology class prior to the implementation of the Enforcement Directive as ex ante *specific* (resembling 33.7% of all portfolios), whereas all other pre-treatment portfolios are generally defined as ex ante *broad*.

Table IA18 displays estimation results using the baseline setup but splitting the sample according to the pre-treatment portfolio breadth defined by the patent scope. The comparison of specific (Columns I-II) and broad (Columns III-IV) portfolios reveals that coefficients vary 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 insignificant.

Further, we investigate this relationship in more detail 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 IA6 (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 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 that are rather broad, but not too broad, use their patenting activities to increase leverage. This finding mirrors the ambiguity in the literature regarding the relationship between the technological scope and patent redeployability stated above.