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Patent disputes as emerging barriers to technology entry? Empirical evidence from patent opposition

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2022/12 May 2022
ISSN(ONLINE) 2284-0400

Patent disputes as emerging barriers to technology entry? Empirical evidence from patent opposition

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May 2, 2022

Abstract

The recent surge of patent disputes plays an important role in discouraging firms from entering new technology domains (TDs). Using a large-scale dataset combining data from the EPO-PATSTAT database and ORBIS-IP and containing patents applied at EPO between 2000 and 2015, we construct a new measure of litigiousness using patent opposition data. We find that the degree of litigiousness and the density of patent thickets negatively affect the likelihood of firms entering new TDs. Across technologies, the frequency of oppositions discourages firms mostly in high-tech industries. Across firms, the risk of opposition falls disproportionately on small rather than large firms. Finally, for large firms, we observe a sort of learning-by-being-opposed effect. This evidence suggests that litigiousness and hold-up potential discourage firms from entering new TDs, shaping Schumpeterian patterns of innovation characterized by a stable number of large-established firms and a lower degree of turbulence.

Keywords: Patent opposition, Technological entry, Innovation Strategies

JEL classification: O31, O33, O34

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1 Introduction

Recent works have detected falling entry rates of new firms and rising market shares of large firms both across Europe and US (Autor et al., 2020; De Loecker et al., 2020; Gutiérrez and Philippon, 2017; Calligaris et al., 2018; Criscuolo, 2018)[1]. One of the reasons for this increasing concentration is the stalling technological diffusion due to distortions in patent appropriability conditions (Andrews et al., 2016). In addition, the surge in patent applications, coupled with increasing patents strategic use, may exacerbate the exclusive nature of patents and their legal frameworks, raising barriers to entry (Akcigit and Ates, 2019; Akcigit and Ates, 2021).

The rich body of empirical research on technological regimes shows that appropriability conditions are crucial to understanding technology-specific innovation patterns. In their seminal paper, Breschi, Malerba, et al. (2000) show that particular combinations of technological opportunities, cumulativeness, knowledge base characteristics, and appropriability induce either "creative destruction" or "creative accumulation" patterns of innovation.[2] To this reasoning, we add that a significant entry barrier also arises because of distortions in patent appropriability conditions. The last decade has witnessed a substantial rise in patent disputes and subsequent transaction costs. Such distortions may lead to higher uncertainty for new entrants (Ceccagnoli, 2009; Blind et al., 2009).

Previous works documented how entry decisions are affected by patent-related specific aspects such as the potential for hold-up due to patent thickets (Cockburn and MacGarvie, 2011; Hall, Graevenitz, et al., 2021) or litigation costs (Lerner, 1995), characterizing high-tech industries. This work contributes to this literature by introducing a new measure of industry litigiousness, constructed using patent opposition data. Several features of the opposition procedure at the European Patent Office (EPO) make these data a good candidate to measure the degree of litigiousness and the risk firms incur in a patent dispute. First, the widespread use of this administrative procedure across low-tech domains allows us to test litigiousness as an entry barrier in various technological domains (TDs), beyond the usual explored high-tech technologies. Second, patent opposition is a frequent event that exceeds court litigation rates in Europe, and several jurisdictions other than the European one recently adopted it[3]. This administrative procedure provides opportunities to challenge newly granted patents to a broad spectrum of countries and heterogeneous firms. Therefore, investigating whether an excessive opposition rate generates some distortions in the technological competition among firms is a crucial research question.

This paper tests whether high litigiousness measured using patent opposition discourages technological entry, inducing a "creative accumulation pattern" of innovation characterized by a stable number of large-

[1] For a recent review, see Van Reenen (2018).

[2] Technological competition assumes the form of "creative destruction" in the Schumpeter Mark I regime, characterized by turbulent environments with relatively low entry barriers. On the contrary, the "creative accumulation" pattern of innovation occurs in Schumpeter Mark II regimes, characterized by stable environments with relatively high entry barriers.

[3] For the detailed list of countries in which the opposition procedure is available see: www.wipo.int/scp/en/revocation_mechanisms/opposition (accessed 25.02.2022).

established firms and industries with a lower degree of turbulence. Following the approach proposed by Hall, Graevenitz, et al. (2021) we control for other relevant dimensions shaping the technological regimes and technological entry, such as technological opportunities, the complexity of the patent network and the density of patent thickets. As an additional contribution, we analyze the interaction between industry-level and firm-level characteristics. In particular, we test the role of knowledge-relatedness and technological diversification in firm's decision to expand into a new TD (Leten et al., 2016). Finally, we also draw attention to the learning process that might occur. We assess whether the firm's previous experience with the opposition procedure gives any advantage to the firm regarding "learning-by-being-opposed" or exacerbates the patent litigiousness effect.

Our empirical analysis is carried out using a hazard rate model of a firms' technology entry as a function of both industries- and firm-level indicators. We identify entry into a new TD as the first time a firm applies for a patent in that technology area. Therefore, entry is defined in terms of technology entry rather than as market entry[4] The model is estimated using a novel dataset built combining data from the EPO-PATSTAT Database (Autumn 2019 edition) and the Bureau Van-Dijk ORBIS-IP[5].

Results indicate that the degree of litigiousness and the density of patent thickets negatively affect the likelihood of firms entering new TDs. Across technologies, the frequency of opposition discourages firms mostly in high-tech industries. Across firms, the risk of opposition falls disproportionately on small rather than large firms. Moreover, small firms do not benefit from past experience with the opposition procedure, while we observe a learning-by-being-opposed effect for large firms. This evidence suggests that litigiousness and hold-up potential discourage firms from entering new TDs, shaping Schumpeterian patterns of innovation characterized by a stable number of large-established firms and a lower degree of turbulence.

The remainder of this paper is organized as follows. Section 2 introduces the opposition procedure and its main features. Section 3 presents a review of the literature on technology entry. Section 4 describes the data, the econometric model, and descriptive statistics. Section 5 presents the econometric results. Conclusions follow.

2 Patent opposition at the EPO and previous literature

Patent systems offer a variety of procedures to question third-party intellectual property rights, mainly by challenging a patent right in court or by contesting the validity of newly granted patents through administrative procedures. Forms of post-grant review mechanisms provide an error-correction mechanism

[4]The relationship between market entry and technology entry is still not clear. While Pavitt (1998); Brusoni et al. (2001) claims that most of the times technological diversification anticipates product and market diversification, Dosi, Grazzi, et al. (2017) 's results suggest that firms are much more diversified in terms of products than in terms of technologies.

[5]For an overview see: www.bvdinfo.com/en-gb/our-products/data/international/orbis-intellectual-property (accessed 25.02.2022).

to amend possible patent office mistakes[6].

EPO offers third parties the possibility to challenge undeserved patents by filing a patent opposition. Interested parties can contest patent validity on the ground of not meeting standard requirements of novelty and non-obviousness within nine months from the patent granting. After nine months from the granting, the only option for patent invalidation is national courts. In response to an opposition, the EPO may decide to uphold the issued patent in its entirety, amend the patent by limiting or removing claims, or invalidate it entirely. Gaessler et al. (2019) examine outcomes data and find equal shares across these three possibilities. Settlements among parties during opposition are not frequent, both because of the short time horizon available for negotiations and the fact that EPO pursues an invalidation even after the opponent's withdrawal (Gaessler et al., 2019). On the contrary, Graham and Harhoff (2014) estimate that 90% of court litigation cases end in settlements in the US.

Several features of patent opposition at EPO justify our decision to measure the degree of litigiousness using the frequency of this administrative procedure. First, it allows us to detect patent disputes among firms in previously neglected TDs based on court litigation data (Lerner, 1995) or patent thickets (Hall, Graevenitz, et al., 2021). Court litigation rates are exceptionally high in specific industries such as Chemicals, Pharmaceutical and Instruments (Bessen and Meurer, 2013). The same holds for patent thickets that are mostly diffused in high-tech TDs, characterized by numerous overlapping patents and dispersed patent ownership. On the contrary, oppositions procedures are widespread across numerous sectors, including low-tech TDs. Figure 1 shows that in our data, the highest rate of opposed patents are in low-tech TDs, such as Food products and Paper.[7] The rate of opposed patents is instead lower in high-tech TDs. Different incentive mechanisms driving opposition in low- and high-tech TDs may explain this result (Harhoff, Graevenitz, et al., 2016; Gaessler et al., 2019). Firms may obtain considerable gains by invalidating patents in discrete TDs, in which one patent covers one invention or product. In these cases, success in invalidating one patent may result in freedom to operate in subsequent follow-on innovation. A lower incentive for firms is instead present in high-tech domains, where inventions are protected through multiple patents, diminishing the benefit of single patent invalidation. Moreover, the opponent firm always provides a public good to all firms interested in the patent removal. However, in TDs with fragmented patent ownership, a firm "who successfully challenges a patent will profit less on average than in a field with highly concentrated ownership" (Harhoff, Graevenitz, et al., 2016). In such contexts, settlements among parties, usually frequent during court litigation, may instead be a reasonable way to solve patent disputes. Despite the need for a mechanism to revise the granting of undeserved patents in TDs characterized by patent thickets and dispersed patent ownership, patent opposition does not constitute an effective institution in these contexts (Harhoff, Graevenitz, et al., 2016).

[6] Recent estimates suggest that approximately 75% of granted German patents would be partially or fully invalidated if challenged in court (Henkel and Zischka, 2019)

[7] Technological domains (TDs) are aggregations of IPC classes following the concordance table by Van Looy et al. (2014). See section "Data" below.

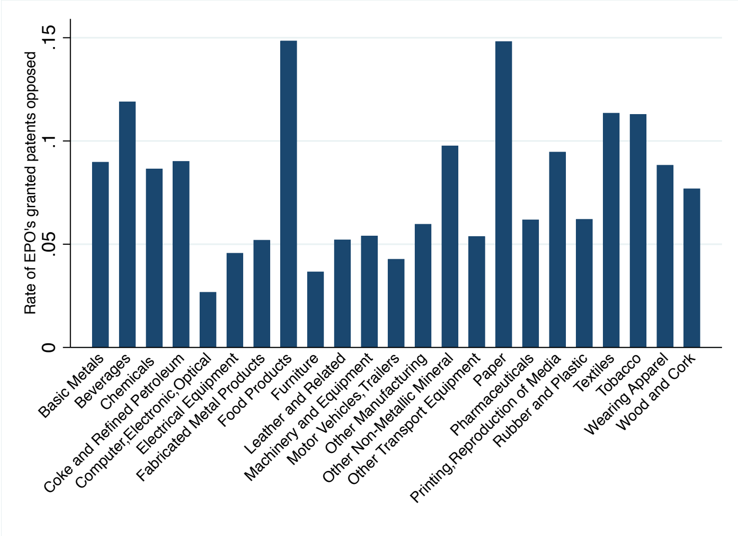


Figure 1: Average rate of opposed patents across fields, 2000-2015. Data retrieved from Orbis-IP.

The second reason behind our choice to measure litigiousness using opposition data is the widespread use of this procedure. Court litigation typically arises in response to a patent infringement and is a rare event. The litigation rate vary from 2% in Germany to 0.08% in UK (Cremers et al., 2017). On the contrary, the opposition procedure provides the opportunity to challenge newly granted patents to any interested party and historically accounts for 6% of granted patents. The reasons for this widespread diffusion is threefold. First, compared to court litigation, the opposition is a low-cost procedure. While average litigation costs are approximately between 50,000 and 500,000 euros, the average cost of the EPO opposition is between 6,000 and 50,000 euros, including patent lawyers' fees (Harhoff, 2009). However, we must remember that legal costs are not the only expenses related to patent disputes. As argued by Bessen and Meurer (2008), firms may "be disrupted as managers and researchers spend their time producing documents, testifying in depositions, strategizing with lawyers, and appearing in court". Notwithstanding lower fees compared to court litigation, these additional costs may be of particular relevance for small firms (Hughes, Mina, et al., 2010). Second, it is a much faster administrative way to invalidate patents than litigation in court. Third, patent opposition is the only way to invalidate a European patent at the transnational level centrally and may be pursued for avoiding its duplication in a bundle of national patent rights (Gaessler et al., 2019).

The success of the EPO opposition procedure (Hall, Graham, et al., 2004) led the United States Patent and Trademark Office (USPTO) to recently introduce similar processes such as Post Grant Review (PGR) and Inter Partes Review (IPR) within the America Invents Act (AIA) in 2012[8]. Given the relevancy of this procedure and its diffusion across firms and countries, it is worth investigating whether an excessive opposition rate generates any distortions for firms.

Scholars have studied different aspects of patent oppositions at the EPO. Patent-level analysis in-

[8]For a detailed description see e.g. Lerner et al. (2015) and Love et al. (2019).

dicates that particularly valuable patents are more likely to be opposed (Harhoff, Scherer, et al., 2003; Harhoff and Reitzig, 2004; Schneider, 2011; Caviggioli et al., 2013). Interesting differences emerge across industries. For the reasons stressed above, opposition decreases in fields characterized by complex technologies with a large number of mutually blocking patents (Harhoff, Graevenitz, et al., 2016; Gaessler et al., 2019). Looking at the effects of invalidation on the subsequent innovation activity of inventors, Nagler and Sorg (2020) suggest instead that post-grant review benefits the patent system by reducing low-quality filings. Strategic implications that underlie the decision to file an opposition were also previously discussed in the literature (Harhoff and Hall, 2002; Calderini, Scellato, et al., 2004; Blind et al., 2009; Sterlacchini, 2016) with different results. Harhoff and Hall (2002) explain high rates of opposition in the cosmetic sector as a result of the strategic behaviour of few large firms. Focusing on the telecommunication industry and comparing patent portfolios of opposed and opponent firms, Calderini, Scellato, et al. (2004) suggest that larger firms are more likely to oppose smaller firms, behaving collusively. Blind et al. (2009) explore patent strategies and find evidence that offensive and blocking patent strategies are related to a higher incidence of oppositions. However, Sterlacchini (2016) rules out the possibility of a strategic abuse of the opposition procedure as it shows that large owners' patents are more likely to be revoked, suggesting that their competitors more thoroughly scrutinize patents owned by market leaders. Nevertheless, to our knowledge, none have assessed whether the threat of opposition may constitute a barrier for potential new entrants or whether firms benefit from previous experiences with this administrative procedure in their decision to enter a new TD.

3 Technology entry and industry patent litigiousness

Breschi, Malerba, et al. (2000) show that combinations of technological opportunities, cumulativeness, knowledge base characteristics, and appropriability conditions determine how industries structure evolves. High technological opportunities and low cumulativness spur technological entry, while a more complex knowledge base is negatively related to entry because firms may lack accumulated absorptive capabilities. Appropriability conditions are also recognized as important determinants of technological competition. Distortions in how firms may exploit patents and their legal framework may represent emerging barriers to entry. The increasing evidence on strategic patent use indicates that firms might have "stretched" patent use well beyond its incentive function through a period of monopolistic exclusivity (Ceccagnoli, 2009; Blind et al., 2009; Torrisi et al., 2016). For instance, the well-known court cases between Samsung and Apple ended up in a real "patent war"[9], suggesting that patent challenges were employed in their battles for market dominance.

Previous studies documented the rise in patent litigation in the US and how the risk of litigation falls disproportionately on small firms (Lanjouw and Schankerman, 2001; Lanjouw and Schankerman, 2004;

[9]https://www.nytimes.com/2018/06/27/technology/apple-samsung-smartphone-patent.html (accessed 25.02.2022).

Bessen and Meurer, 2013). Recently, Galasso and Schankerman (2018) found that the loss of patent rights due to court invalidation of patents significantly increases the likelihood of exit for small firms.
Some authors focus on distortions due to the patent system functioning and characteristic and how these may affect technology entry. Lerner (1995) documents that the threat of litigation discourages firms in the biotechnology industry from entering, thus providing a disincentive rather than an incentive for R&D. Cockburn and MacGarvie (2011) study entry in the software industry and found that a 1% increase in the number of patents reduces the rate of entry by 0.8%. In a similar vein, Hall, Graevenitz, et al. (2021) found that greater technological opportunity and complexity both encourage entry, while higher transaction costs arising from hold-up potential reduce entry. Other works highlight that patent-related entry barriers mainly occur in industries characterized by complex technologies where each product is protected by hundreds or even thousands of overlapping patents, often with fuzzy boundaries. In such contexts, if patents ownership is dispersed across many competing firms, the "dense web of overlapping intellectual property rights" (Shapiro, 2000) forms so-called "patent thickets", leading to innovators hold-up, complex negotiations over licenses and patent litigation (Bessen and Meurer, 2013). Particular challenges emerge in these contexts by standard essential patents (Lerner et al., 2015).
In this paper, we expand this perspective and focus on the disputes arising from patent opposition procedures. The high frequency of this procedure suggests an intense activity of monitoring competitors' patenting activity across TDs, generating uncertainty for new entrants (Ceccagnoli, 2009; Blind et al., 2009). Particular concern regards small firms, for which the direct cost of the procedure, together with a lack of capabilities in enforcing their patent rights compared to large firms, may constitute an additional obstacle (Hughes, Mina, et al., 2010).

Despite technological opportunities, the density of patent thickets and frequency of patent disputes, firms may have heterogeneous behaviours in their decision to enter a new TD depending on their past experiences, breadth of knowledge and capabilities in related TDs. As previous studies have pointed out, firms engage in coherent technological activities (Teece, Rumelt, et al., 1994), and "diversify around groups of technologies that share a common or complementary knowledge base, rely upon common scientific principles or have similar heuristics of search" (Breschi, Lissoni, et al., 2003). It follows that a firm's knowledge-relatedness is a key factor affecting firms' technological entry (Leten et al., 2016), which may moderate the impact of industry characteristics. Dosi, Grazzi, et al. (2017) find that as firms develop new technologies, the coherence between neighbouring activities is high for relatively low levels of diversification but remain present also for sufficiently diversified firms. The breadth of the knowledge domain of the firm is also a crucial factor driving firms' decision to enter a new TD. A diversified technology base implies a broader set of knowledge, capabilities and heuristics that can be (re)combined to generate innovations, enhancing the likelihood of a firm to enter new TDs. However, has suggested in Leten et al. (2016), highly diversified firms may be less likely to enter (the remaining) sectors because they have already entered the most attractive domains. Besides technological capabilities, IP managerial capabilities (e.g. how to enforce patent rights and face patent disputes) may also be necessary for first-time patenting firms. Therefore, in highly litigious TDs, relevant knowledge may derive from previous experience with the opposition procedure, reducing firms' uncertainty.

In our paper, we provide evidence on how the interaction of firm-level characteristics and industry-level dimensions influences a firm's likelihood to enter a new TD. Our focus on technology entry rather than market entry avoid issues related to data on product market outcomes. Nevertheless, given the recognized role of new entrants to largely contribute to radical rather than incremental inventions (Henderson, 1993), reduced technology entry is likely to have negative long-run consequences on innovation and product market competition.

4 Data and Empirical Model

4.1 Data

We combine patent and firm-level data to address how litigiousness affects firms' entry into new TDs. Our starting dataset contains the universe of patents applied at the EPO (including the PCT applications received at the EPO) filed between 2000 and 2015[10]. These data are retrieved from the EPO-PATSTAT database (Autumn 2019 edition) and contain 2,348,476 patents. We assign patents to TDs using the concordance table developed by Van Looy et al. (2014), linking patent IPC codes[11] with the current NACE Rev.2 classification system available in the EPO-PATSTAT database[12].

We obtain firm-level data and patent opposition data from ORBIS-IP, a recently released data set provided by the Bureau Van Dijk, combining rich firm-level and patent-level information and covering the entire population of registered firms[13]. For each EPO patent publication, we linked a firm identifier of the patent applicant(s) that we used to obtain applicants' financial information from the ORBIS Database [14]. For about 14% of the initial EPO sample, the ORBIS-IP database does not report a firm identifier in the ORBIS-IP database, so we remove those observations[15]. We also remove observations whose applicants are universities, research centres, state and government institutions (less than 1% of our observations).

We use this dataset of EPO patent applications to identify technological entry as the first time a firm files a patent in a specific TD at EPO[16]. Our final dataset contains information about 173,555 firms entering

[10]We limit our analysis up to 2015 to avoid truncation problems arising from patent publication lag.

[11]We exclude patents with no information about the IPC technology classes, which are less than 1% of the whole sample.

[12]The EPO-PATSTAT database provides in table TLS229_APPLN_NACE2 a revision of the concordance table by Schmoch et al. (2003). We treat patents assigned to more than one TD as distinct applications in the definition of technology entry. We use instead weights provided in the above mentioned table availabile in EPO-PATSTAT when we construct the TD-level variables described in the next section.

[13]For info see www.bvdinfo.com

[14]We rely on the "BVD identifier", a firm unique identifier of throughout all the Bureau Van Dijk Databases.

[15]A manual check of a subset of these cases indicates that the missing identifier relates to assignees being individual inventors

[16]Note that we evaluate entry since firm's foundation. We use instead the date of EPO's foundation (1978) for those firms that were established prior to the birth of the patent office.

26 TDs between 2000 and 2015.

4.2 TD-level variables

Our analysis's primary variable of interest is the new measure of litigiousness based on patent opposition, which allows us to capture the level of administrative patent disputes directly. The variable $Litigiousness_{k,t}$ is constructed as the percentage of EPO's patent grants in a given TD k at the time of entry t.

Patents might affect enter into TDs differently, depending on the level of negotiations over licenses and patent litigation among firms, the incidence of patent thickets and related hold-up. To account for these differences, we follow the approach proposed by Hall, Graevenitz, et al. (2021) and add to our specification the measure developed by Graevenitz et al. (2011) to capture the hold-up potential of patent thickets. This indicator measures how often a patent applicant simultaneously "blocks" and "is blocked" by the same firm in a specific TD. The extent to which an applicant is in this stalling position indicates the presence of overlapping patent rights. To build the thicket indicator, we exploit the information available at the EPO about critical references. EPO search reports classify references (i.e. citations). The X-, Y- and I- categories indicate references prejudicing novelty, inventive step or particularly relevant if combined with another document of the same category. Using these critical references, we can construct a network of applicants, where at time t each unidirectional link between two applicants A and B corresponds to one or more critical references to firm A's patents in the set of patents applied by firm B in the years t, $t-1$ and $t-2$. The variable $Patent\ Thicket_{k,t}$ is the number of fully connected triads in the network of the critical references between all the applicants in TD k at time t. We normalize the count of triples by the total number of applied patents in each TD, so that the triples variable represents the intensity with which firms potentially hold blocking patents relative to aggregate patenting activity in the TD. We retrieve information on the type of references from the EPO-PATSTAT Database.

Technological entry may be related to technological complexity where patents are highly related to neighbouring patents and where technological opportunities abound (Teece, Sherry, et al., 2014). To control for these possibilities, we also include controls for the level of technological complexity and technological opportunities, following the approach by Hall, Graevenitz, et al. (2021). We measure the level of complexity as the density of patent citations' network for each TD k at time t. The variable $Network\ Density_{k,t}$ is the number of citations among patents in k at time t during the prior 10 years, normalised by the maximum number of possible citations in k (which is $N_{kt}(N_{kt}-1)/2$, where N_{kt} is the number of patents that have been applied for in k between 1978 and year t). To minimize correlation with the variable $Patent\ Thicket_{k,t}$, we calculate the variable $Network\ Density_{k,t}$ using USPTO data retrieved from the EPO-PATSTAT Database[17].

[17]US patent law requires applicants to disclose all the known prior art related to the invention in question ("duty of candor"); therefore, US patent applications generally report more references than the applications of non-US patent offices.

Finally, we control for technological opportunities which should capture the "width, depth and richness of the sea in which incumbents and entrants go fishing for innovation"(Dosi, Marengo, et al. (2006), pp 1119). Following Hall, Graevenitz, et al. (2021) we measure opportunities in two ways. The variable $Techopp1_{k,t}$ is the logarithm of the aggregate EPO patent applications in k at time t. The variable $Techopp2_{k,t}$ is the past 5-year growth rate of scientific publication citations in patents at the EPO in the TD k at time t. In fact, besides opportunities stemming from the very search efforts undertaken by incumbent firms in the past and from suppliers/users relationships, significant technological opportunities are generated by research institutions outside the business sector (Rosenberg, 1982; Breschi, Malerba, et al., 2000).

4.3 Firm-level variables

Besides industry-level characteristics, also firm-level characteristics such as firms' technological knowledge, specialization capabilities and heuristics possibly reflecting firm's past experiences (Dosi, 1982) might affect the decision to enter specific TDs. To control for this possibility, we also include several firm-level variables in our estimation model.

Following the methodology employed in Breschi, Lissoni, et al. (2003), we measure firm's technological relatedness to each potential new TD, exploiting the co-occurrence of the International Patent Classification (IPC) classes assigned to each patent during examination. The indicator's logic is that the frequency of co-occurrence of the IPC classes proxies the strength of the knowledge relationship between the IPC classes. Note that while co-occurrence can be calculate using IPC classes, in our case we will focus on TDs which are nevertheless derived from patents IPC classification. To evaluate TDs co-occurrence, we first build a square and symmetrical matrix whose cells ($C_{j,k}$) report the number of patent documents classified in both TDs j and k. Second, we measure the relatedness between TDs j and k as the co-occurrence patterns between TDs j and k. We calculate:

$$S_{j,k} = \frac{\sum_{m=1}^{26} C_{jm} C_{km}}{\sqrt{\sum_{m=1}^{26} C_{jm}^2}\sqrt{\sum_{m=1}^{26} C_{km}^2}} \tag{1}$$

where $S_{j,k}$ is the cosine of the angular separation between the vectors representing the co-occurrences of TDs j and k with all the other TDs and it ranges between 0 and 1. It is equal to 0 when TD j is completely unrelated to the TD k and their co-occurrence vectors are orthogonal (i.e. cos(90)=0) and it is equal to 1 when TD j and TD k are maximally related and their co-occurrence vectors are overlapping (i.e. cos(0)=1). Table 1 display the relatedness among each pair of TDs , whose elements are the various $S_{j,k}$ (j = 1,..., 26; k = 1,..., 26). Not surprisingly, the highest levels of relatedness are found between Food products and Beverage and between the former and Pharmaceutical. High co-occurrences exist also

The use of USPTO citation data also allows to have a denser network, as USPTO patents tend to make and receive more citations.

Table 1: Knowledge-relatedness matrix based on co-occurence of classification codes. cosine indices x 100

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26
1 Food	100																									
2 Beverages	23.68	100																								
3 Tobacco	1.01	0.19	100																							
4 Textiles	0.30	0.17	0.22	100																						
5 Wearing	0.00	0.00	0.04	5.42	100																					
6 Leather	0.02	0.00	0.00	0.82	3.92	100																				
7 Wood, Cork	0.08	0.15	0.03	1.23	0.12	0.06	100																			
8 Paper	0.85	0.11	1.53	6.28	0.05	0.00	1.16	100																		
9 Printing	0.10	0.00	0.12	2.15	0.13	0.22	0.36	7.52	100																	
10 Coke, Petroleum	0.35	0.07	0.04	0.18	0.00	0.00	0.13	0.71	0.00	100																
11 Chemicals	5.82	2.03	0.43	9.12	1.04	0.50	1.69	5.57	5.75	11.60	100															
12 Pharmaceutical	14.41	3.83	0.33	0.83	0.08	0.03	0.05	0.84	0.34	0.74	13.98	100														
13 Rubber Plastic	0.67	0.47	0.15	3.42	1.51	3.61	2.15	0.68	1.28	0.17	8.30	0.32	100													
14 Other Mineral	0.26	0.08	0.11	9.30	2.61	0.74	3.09	3.59	4.28	0.34	12.65	0.57	9.31	100												
15 Basic Metals	0.05	0.05	0.01	0.07	0.05	0.08	0.03	0.06	0.10	0.53	2.64	0.17	1.22	4.53	100											
16 Fabricated Metal	0.06	0.06	0.07	0.73	1.37	0.36	0.50	0.19	0.21	0.24	2.76	0.13	3.74	4.85	11.95	100										
17 Computer,Electr.	0.49	0.13	0.20	0.40	0.47	0.19	0.09	0.34	2.11	0.21	6.02	6.63	2.72	4.37	1.95	3.26	100									
18 Electrical Equip.	1.36	0.26	0.71	1.39	0.64	0.15	0.09	0.42	0.43	0.30	5.81	0.39	2.36	3.47	2.05	3.79	12.22	100								
19 Machinery Equip.	2.47	0.96	1.31	4.15	1.65	1.02	2.57	3.31	7.87	2.84	10.95	1.75	7.84	8.06	9.34	8.25	13.37	8.85	100							
20 Motor Vehicles	0.03	0.01	0.03	0.81	0.19	0.04	0.06	0.05	0.12	0.50	1.14	0.03	3.20	1.89	1.40	4.43	5.27	9.13	13.52	100						
21 Other Transport	0.02	0.00	0.00	0.24	0.58	0.32	0.06	0.04	0.02	0.13	0.97	0.02	1.80	1.42	0.28	3.18	1.92	2.78	6.04	6.93	100					
22 Furniture	0.09	0.00	0.05	0.52	0.46	0.32	0.64	0.19	0.14	0.00	0.17	0.01	0.81	0.87	0.06	3.83	0.54	3.02	1.67	2.76	1.19	100				
23 Other Manufact.	1.65	0.59	2.53	2.59	3.84	1.35	0.21	1.00	2.09	0.27	6.50	5.44	5.97	5.50	0.92	2.51	11.99	4.54	9.91	2.09	1.65	2.91	100			
24 Civil Engineering	0.02	0.00	0.00	0.17	0.00	0.00	0.00	0.00	0.00	0.03	0.97	0.01	0.39	1.32	0.21	0.53	0.34	0.85	3.93	0.15	2.15	0.38	1.13	100		
25 Construction	0.01	0.02	0.01	3.05	0.17	0.05	4.33	0.81	1.15	0.01	1.61	0.02	1.75	8.56	0.23	6.48	0.67	1.91	4.51	0.66	1.27	1.55	1.96	3.80	100	
26 Computer,Programming	0.14	0.04	0.04	0.04	0.07	0.12	0.01	0.05	0.38	0.04	0.14	0.11	0.18	0.06	0.03	0.17	10.16	1.55	4.41	0.52	0.47	0.51	1.95	0.09	0.06	100

The classification codes refer to the 26 manufacturing sectors (NACE Rev.2 classification) identified by the concordance table of Van Looy et al. (2014).

for Chemicals and Textile. Moreover, coherence seem to be present between Computer, Elettronic and Optical's technologies and Machinery and Equipment or Computer and Programming.

$S_{j,k}$ is calculated at TD-pair level; however, in our analysis we are interested in evaluating the relatedness of firm i's technological knowledge with all the possible TDs in which it has not yet entered. Therefore for each firm i we identify its core technology ($c_{i,t}$) as the TD in which it has filed the largest number of patents in period t. We then define $Relatedness_{i,t,k}$ as the $S_{c_{i,t},k}$ which capture the relatedness at time t of firm's core TD $c_{i,t}$ and any potential new TD k.

Besides relatedness, we also control for firm's technology diversification to capture the breadth of its knowledge base (Breschi, Lissoni, et al., 2003; Dosi, Grazzi, et al., 2017). Our variable $Diversification_{i,t}$ is equal to the number of fields in which the firm is active at time t. To control for the size of the firm in terms of patent portfolio, we add $Portfolio\ Stock_{i,t}$, the patent stock applied for at the EPO at time t by firm i, calculated with a 15% depreciation rate[18]. Finally, we also control for firms' country of origin dummies categorized as Europe, US, Japan, China, South Korea and Other countries[19]. Finally, we control for the entry year with a set of year dummies, referring to the priority year of the patent.

4.4 Empirical model

Our empirical analysis follows previous literature on the determinants of technology entry (Cockburn and MacGarvie, 2011; Leten et al., 2016; Hall, Graevenitz, et al., 2021), therefore we use a Cox proportional hazards model stratified by industry.[20] The dependent variable is a dichotomous variable taking the value one if a firm has entered a TD k at time t and 0 otherwise.

The model estimates the probability that a firm enters (i.e. the first time a firm files a patent) in a specific TD conditional on not having entered yet, as a function of the firm's characteristics and the time since the firm was "at risk," which is the time since the founding of the firm. In some cases, our data do not go back as far as the founding date of the firm, and in these cases, the data are "left-censored." When we do not observe the firm's entry into a particular technology sector by the last year (2015), the data are "right-censored."

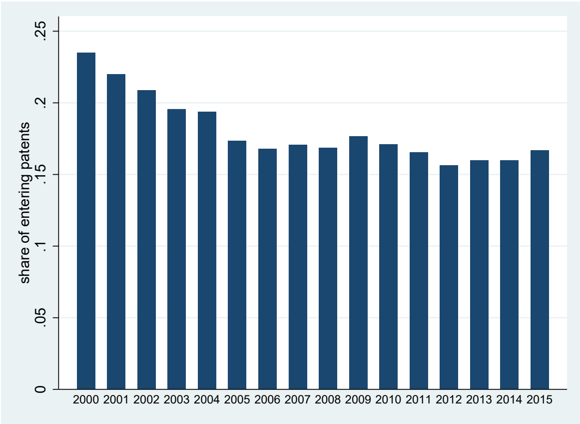
Regarding the lag structure of our model, we use variables at time t. For our main variable of interest $Litigiousness_{k,t}$, we also run the analysis using the lagged variable at $t-3$, and the results are the same. We decided to use simultaneous variables because we loose a significant number of observations using the lagged ones. Furthermore, the variation of this variable over time is relatively low, and we prefer to measure our main variable at time t, assuming that the firm is monitoring patent litigiousness at the time of patent application.

[18] $KPAT_t = PAT_t + (1-\delta)KPAT_{t-1}$ where PAT_t is the annual number of patents applied for at the EPO by the firm, $KPAT_t$ is the patent stock and δ is the depreciation rate (see Hall, Jaffe, et al. (2005))

[19] 10% of the firms in our dataset belongs to the residual category. Detailed information are present in Appendix B.

[20] We test the validity of the proportional hazard assumption in Appendix C. Results are robust to other specification such as parametric survival models. These results are reported in Appendix D.

Figure 2: Average percentage of firm's first-time patenting (entering patents) across time



Our own elaboration on patents applied for at EPO between 2000 and 2015

As for the use of stratification, it allows firms in each TD to have a different time distribution, conditional upon the regressors, until TD entry. This means that each TD industry has its own "failure" time distribution, where failure is defined as entry into patenting in a TD. We cluster standard errors at firm level to control for correlations in error terms due to unobserved firm characteristics[21].

Our data for estimation are for the 2000-2015 period, but many firms have been at risk of patenting for many years before that. As the EPO was founded in 1978, we chose that year as the earliest date any of our firms is at risk of entering into patenting. We defined the initial year as the maximum between the firm's founding year and 1978. For those firms missing the foundation date (10% in our dataset) we use 1978 as the initial year.

Our final sample has 4,449,257 firm-TD observations. For each firm-TD pair, our dichotomous dependent variable captures whether the firm enters the TD or not during the period. The total number of failures (technology entry) is 302,513, corresponding to 6% of our observations. Our set of potential entrants corresponds to any firm-sector pair in which the dependent variable is zero.

4.5 Descriptive statistics

Table 2 gives an overview of our sample of patents by sector in the whole period of analysis. Fields with the highest number of patents applied for are Computer, Electronic and Optical, Machinery and Equipment, Chemicals and Pharma. To assess the entry level in a new TD, we compute the percentage of patents representing the firm's first-time patenting in a give TD ("entry-patents"). We find high heterogeneity in this indicator, suggesting different degrees of turbulence across fields. The incidence of entry ranges between 0.08 of the "Computer, Electronic and Optical" domain to 0.69 of "Civil Engineering". The average across TD over time, reported in Figure 2, suggests a general decrease of the percentage of first-time patenting in the last fifteen years, thereby indicating a lower degree of technology entry rate.

[21] Using the clustering at both firm and industry level do not change the results.

Table 3 displays the mean values of the industry-level explanatory variables in our period of analysis. In the last column, we specify whether each identified TD corresponds to low-tech or high-tech industries, according to the OECD's classification (Galindo-Rueda and Verger, 2016).

We observe lower entering rates in TDs with both the highest number of patents in the period (*Techopp1*) and the highest density of patent thickets. On the contrary, TDs with a lower share of entry-patents display smaller values of network density. Interestingly, sectors characterized by many overlapping patents have a lower citations density among them, suggesting a lower degree of connections among patents in the network of references. This finding is consistent with the high presence of sleeping patents and strategic non-use of patents (Torrisi et al., 2016) in sectors characterized by many patent thickets. Instead, Food Products and Paper are the sectors with the highest rate of opposed patents (15%), but reveal a low number of patent triads. We find the lowest values of litigiousness in TDs characterized by many overlapping patents and lower density in their network of citations. As stressed above, in complex technologies, characterized by a high density of patent thickets, firms have a lower incentive to proceed in an opposition procedure (Gaessler et al., 2019). Table 4 shows the correlations for the explanatory variables included in our model. None of the reported correlations is excessively high. We observe some correlation between *Techopp1* or *Techopp2* and *Network density.* Slightly higher correlations are found among firm-level covariates. In particular, there is a negative correlation between *Portfolio stock* and both *Diversification* and *Relatedness.* The correlation between *Diversification* and *Relatedness* is instead positive. We thus ran robustness checks excluding the latter two indicators from the list of control variables, finding that this has no impact on the main results.

The complete descriptive statistics for the variables used in the empirical analysis are in table A1.

5 Results

Table 5 reports the estimated coefficients for the hazard of entry into new TDs [22]. In the first two columns, we test the role of technological opportunities and network density as drivers for entry. In line with previous results in the literature (Leten et al., 2016; Hall, Graevenitz, et al., 2021), all three indicators display a positive and significant coefficient, meaning that the richness of technological opportunities increases a firm's probability to enter into a new TD. Interestingly, the negative effect of patent thickets is significant only once controlling for the number of patents applied for in an industry (Column 2), suggesting that the presence of overlapping patents reduces a firm's likelihood to entry new TDs in sectors characterized by a certain number of yearly applications. In columns 3-5 we introduce the firm-level covariates measuring the degree of diversification, relatedness and our main variable of interest, litigiousness. In all our specifications, firm's portfolio stock is negatively associated with the probability

[22] The coefficients in table 5 are estimates of the yearly hazard rate elasticity. Hazard ratios for these variables can be calculated as $\exp(\beta_i)$.

Table 2: Sample Population of Patents by TD in the period 2000-2015

	nr of patents	nr of entry-patents	share of entry-patents	nr of firms
Basic Metals	24,014	4,357	0.18	2,340
Beverages	1,446	934	0.65	379
Chemicals	272,191	27,911	0.10	24,115
Civil Engineering	1,613	1,112	0.69	255
Coke and Refined Petroleum	10,977	2,220	0.20	1,600
Computer, Programming, Consultancy	14,387	6,487	0.45	2,338
Computer, Electronic, Optical	755,060	61,193	0.08	45,452
Electrical Equipment	174,767	22,563	0.13	11,183
Fabricated Metal Products	53,899	12,885	0.24	8,843
Food Products	35,619	7,339	0.21	7,411
Furniture	7,529	3,081	0.41	1,501
Leather and Related	4,029	1,191	0.30	999
Machinery and Equipment	381,327	49,138	0.13	29,589
Motor Vehicles,Trailers	85,039	9,142	0.11	3,058
Other Manufacturing	152,171	30,994	0.20	14,953
Other Non-Metallic Mineral	34,571	7,954	0.23	3,785
Other Transport Equipment	18,557	4,906	0.26	1,962
Paper	7,327	1,548	0.21	1,010
Pharmaceuticals	221,350	23,073	0.10	15,142
Printing, Reproduction of Media	12,043	2,200	0.18	1,640
Rubber and Plastic	49,036	10,290	0.21	6,325
Specialised Construction Activities	9,645	5,029	0.52	2,276
Textiles	11,881	2,666	0.22	2,553
Tobacco	4,178	536	0.13	388
Wearing Apparel	3,583	1,590	0.44	1,285
Wood and Cork	2,236	800	0.36	623

Note: Entry-patent defined as firm's first-time patent in a given technological domain (TD).

Table 3: Descriptives of TD-level explanatory variables, mean values for the period 2000-2015

	litigiousness	network density	techopp1	techopp2	patent thickets	technology intensity
Basic Metals	0.09	0.07	1,176.3	0.48	58.9	low-tech
Beverages	0.12	0.71	123.2	0.89	2.8	low-tech
Chemicals	0.09	0.01	14,185.7	0.83	5,310.3	high-tech
Civil Engineering	0.03	0.44	200.6	1.00	0.2	-
Coke and Refined Petroleum	0.09	0.23	412.6	1.76	88.6	low-tech
Computer, Programming, Consultancy	0.07	0.38	1,565.6	1.16	122.6	-
Computer, Electronic, Optical	0.03	0.01	44,620.8	0.67	39,085.1	high-tech
Electrical Equipment	0.05	0.02	12,070.3	0.71	4,892.9	high-tech
Fabricated Metal Products	0.05	0.05	3,084.5	0.61	94.4	low-tech
Food Products	0.15	0.09	1,458.8	1.09	132.4	low-tech
Furniture	0.04	0.22	716	0.44	3.9	low-tech
Leather and Related	0.05	1.44	256.8	2.45	2.9	low-tech
Machinery and Equipment	0.05	0.01	29,192.4	0.48	10,213.2	high-tech
Motor Vehicles, Trailers	0.04	0.03	7,519	0.22	5,556.6	high-tech
Other Manufacturing	0.06	0.02	14,679.9	0.89	1,758.9	low-tech
Other Non-Metallic Mineral	0.10	0.04	2,068.1	0.64	226.6	low-tech
Other Transport Equipment	0.05	0.10	1,763.6	0.28	103.7	high-tech
Paper	0.15	0.34	318.9	0.95	8.1	low-tech
Pharmaceuticals	0.06	0.02	15,568.3	0.98	6,164.4	high-tech
Printing, Reproduction of Media	0.09	0.19	428.8	0.88	84.4	low-tech
Rubber and Plastic	0.06	0.05	2,535.7	0.77	173.4	low-tech
Specialised Construction Activities	0,07	0.18	1,221.6	0.45	4.8	-
Textiles	0.11	0.19	384.8	0.57	34.6	low-tech
Tobacco	0.11	1.60	197.1	5.54	18.1	low-tech
Wearing Apparel	0.09	0.71	184.9	0.99	0.3	low-tech
Wood and Cork	0.07	0.94	82.7	1.56	0.4	low-tech

Note: Litigiousness is the rate of opposed patents at the EPO. Network density is 1,000 times the number of within technology citations divided by the potential number of citations (USPTO data). Techopp1 is the number of aggregate patent applications at the EPO. Techopp2 is 5-year growth rate of scientific publication citations in EPO patents. Patent thickets is the number of fully connected patent triads in terms of citations at the EPO (Graevenitz et al., 2011). Each TD is assigned to either low-tech or high-tech, according to the OECD classification (Galindo-Rueda and Verger, 2016).

Table 4: Correlation matrix of coefficients of cox model

	patent thickets$_{k,t}$	techopp1$_{k,t}$	techopp2$_{k,t}$	network density$_{k,t}$	litigiousness$_{k,t}$	portfolio stock$_{i,t}$	diversification$_{i,t}$	relatedness$_{i,t}$
patent thickets$_{k,t}$	1							
techopp1$_{k,t}$	-0.18	1						
techopp2$_{k,t}$	0.05	0.02	1					
network density$_{k,t}$	0.13	-0.29	-0.33	1				
litigiousness$_{k,t}$	-0.1	-0.03	0.08	-0.08	1			
portfolio stock$_{i,t}$	0	0.01	-0.04	-0.01	-0.02	1		
diversification$_{i,t}$	0.03	-0.03	0.07	-0.01	0.02	-0.77	1	
relatedness$_{i,t}$	0.02	-0.04	0.06	-0.02	0.03	-0.17	0.43	1

Table 5: Hazard of entry a new TD

	1	2	3	4	5
log(techopp1$_{k,t}$)		0.265***	0.260***	0.259***	0.253***
		(0.030)	(0.030)	(0.031)	(0.031)
log(techopp2$_{k,t}$)	0.0154***	0.0133***	0.0132***	0.0124***	0.0121***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
log(network density$_{k,t}$)	0.309***	0.286***	0.287***	0.284***	0.295***
	(0.026)	(0.027)	(0.027)	(0.027)	(0.027)
log(portfolio stock$_{i,t}$)	-0.0917***	-0.0917***	-0.151***	-0.143***	-0.143***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
log(patent thickets$_{k,t}$)	-0.00333	-0.0125***	-0.0123***	-0.0128***	-0.0122***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
log(diversification$_{i,t}$)			0.202***	0.327***	0.327***
			(0.006)	(0.007)	(0.007)
log(relatedness$_{i,t}$)				0.106***	0.106***
				(0.001)	(0.001)
log(litigiousness$_{k,t}$)					-0.0328***
					(0.012)
Observations	4,449,257	4,449,257	4,449,257	4,449,257	4,449,257
LogLikelihood	-2,756,040	-2,755,991	-2,754,861	-2,752,472	-2,752,469
Country dummies	YES	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES	YES
Industry dummies	stratified	stratified	stratified	stratified	stratified

Note: Coefficients for the hazard of entry are reported. Time period: 2000-2015.
Minimum entry year: 1978. Standard errors are clustered on firms and reported in parenthesis
Legend: *** p<0.01, ** p<0.05, * p<0.1

of entry. On the contrary, the degree of diversification of the firm positively correlates with the probability of entry, suggesting that firms active in multiple markets have a greater propensity to explore new TDs. As expected, the degree of relatedness between the firm's core technology and the potential new TD positively affects the probability of entry. Firms display some coherence in the way they diversify. Our variable of interest shows a significant negative sign for the new litigiousness indicator measured using patent opposition. The degree of litigiousness of an industry is indeed negatively associated with firm's probability to enter. A one standard deviation increase in the log of litigiousness is associated with a 1,7% decrease in the hazard of entry (-0.0328 x -0.54)[23]. Since the average probability to entry is 6%, the magnitude of this result is substantial.

Overall our results suggest that greater opportunities and complexity of patents' network increase the probability of entry, while firms are discouraged from entering into TDs characterized by higher litigiousness and density of patent thickets. Moreover, the degree of diversification and relatedness are important drivers for entry.

5.1 Unboundling the effect of litigiousness

The preceding results show that while technological opportunities and related capabilities drive technology entry, patent litigiousness and density of patent thickets discourage firms from entering new TDs, on average. However, the impact of these factors affecting entry may differ across technologies and firms. In this section we unbundle the average effect of our variables by exploring different dimensions of hetero-

[23]Descriptive statistics including std. dev. values are present in Appendix A.

geneity. Moreover, we test whether learning-by-being-opposed helps mitigating the negative effect of the degree of litigiousness of an industry.

5.1.1 Applicants with heterogeneous patent portfolios

Previous studies have highlighted that the conditions for patenting work differently depending on the size of the firm (Bessen and Meurer, 2008; Athreye et al., 2020). Sources of obstacles for small firms in this respect are cost barriers, internal capabilities and disadvantages in enforcing their IP rights compared to large established firms (Hughes, Mina, et al., 2010). Moreover, firm's degree of portfolio diversification may determine heterogeneous capabilities to enter into new TDs. In this section we test whether the degree of litigiousness falls disproportionately on firms with either a smaller patent portfolio or a lower degree of diversification across TDs. We test the role of the portfolio's size by interacting our indicator of *Litigiousness* with the firm-level indicator *Portfolio stock*. Looking at the interaction coefficients between *Litigiousness* and *Diversification* we test the hypothesis of advantages stemming from the firm's diversified knowledge base. Column 1 of Table 6 shows that smaller firms in terms of patent portfolio are less likely to enter TDs characterized by patent litigiousness compared to larger firms. Interestingly, being highly diversified across TDs does also mitigate the discouraging effect of litigiousness.

To further test these effects, we then split the sample among small and medium-large firms in terms of patent portfolio. The former are defined as those firms belonging to the first quartile of the patent portfolio distribution[24] whereas all the other firms fall in the medium-large category. As shown in the last two columns, while the negative effects of litigiousness and density of patent thickets are confirmed for small firms, the two coefficients are not significant for medium-large firms. Our findings suggest that firms with a smaller patent portfolio or with a less diversified one across technologies are more affected by the frequency of patent disputes in their decision to diversify in new TDs. These results are confirmed once we use alternative proxy for size using firm-level financial data (see Appendix E). One possible interpretation is that smaller firms are disproportionately affected by the fee structure of the EPO's opposition procedure[25]. Moreover, a more diversified knowledge base implies capabilities that moderate the negative effect of litigiousness on the decision to further diversify in new TDs.

5.1.2 Learning-by-being-opposed

In this section we test whether firm's past exposure to patent opposition is able to alleviate the negative effect of litigiousness. In other words, we assess whether we observe a sort of "learning-by-being-opposed" effect. Table 7 show the results of a new augmented specification in which we add a dummy equal to one if the firm has received at least one opposition in other TDs prior to entry. Interestingly, previous exposure

[24] Firms with less than four patents in their portfolio stock at EPO.

[25] In the case of USPTO new Post-Grant-Review (PGR), Lerner et al. (2015) reports some criticisms on the potential impact of fees on small businesses.

Table 6: Hazard of entry a new TD and patent portfolio heterogeneity

	Full sample		Small firms	Medium-large firms
	1	2	3	4
log(techopp1$_{k,t}$)	0.258***	0.251***	0.348***	0.122**
	(0.031)	(0.031)	(0.038)	(0.055)
log(techopp2$_{k,t}$)	0.0122***	0.0120***	0.0219***	-0.00174
	(0.002)	(0.002)	(0.003)	(0.004)
log(network density$_{k,t}$)	0.297***	0.296***	0.301***	0.130***
	(0.027)	(0.027)	(0.032)	(0.050)
log(portfolio stock$_{i,t}$)	0.0228***	-0.145***	1.074***	0.236***
	(0.007)	(0.003)	(0.016)	(0.005)
log(patent thickets$_{k,t}$)	-0.0119***	-0.0122***	-0.0140***	-0.00373
	(0.003)	(0.003)	(0.004)	(0.006)
log(diversification$_{i,t}$)	0.329***	0.550***	0.232***	0.0775***
	(0.007)	(0.018)	(0.007)	(0.009)
log(relatedness$_{i,t}$)	0.106***	0.106***	0.119***	0.0453***
	(0.001)	(0.001)	(0.002)	(0.002)
log(litigiousness$_{k,t}$)	-0.116***	-0.0991***	-0.0308**	-0.0182
	(0.013)	(0.013)	(0.015)	(0.019)
log(litigiousness$_{k,t}$)* log(portfolio stock$_{i,t}$)	0.0582***			
	(0.002)			
log(litigiousness$_{k,t}$)* log(diversification$_{i,t}$)		0.0753***		
		(0.006)		
Observations	4,449,257	4,449,257	1,181,288	3,267,969
LogLikelihood	-2,752,207	-2,752,398	-1,826,517	-727,781
Country dummies	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES
Industry dummies	stratified	stratified	stratified	stratified

Note: Coefficients for the hazard of entry are reported. Time period: 2000-2015. Minimum entry year: 1978. Standard errors are clustered on firms and reported in parenthesis.
Legend: *** p<0.01, ** p<0.05, * p<0.1

Table 7: Hazard of entry a TD and opposition experience

	1	2	3	Small firms
log(techopp1$_{k,t}$)	0.252***	0.246***	0.256***	0.365***
	(0.031)	(0.031)	(0.031)	(0.038)
log(techopp2$_{k,t}$)	0.0121***	0.0123***	0.0120***	0.0236***
	(0.002)	(0.002)	(0.002)	(0.003)
log(network density$_{k,t}$)	0.295***	0.295***	0.289***	0.300***
	(0.027)	(0.027)	(0.027)	(0.032)
log(portfolio stock$_{i,t}$)	-0.145***	-0.145***	-0.158***	-0.247***
	(0.003)	(0.003)	(0.003)	(0.007)
log(patent thickets$_{k,t}$)	-0.0122***	-0.0120***	-0.0125***	-0.0141***
	(0.003)	(0.003)	(0.003)	(0.004)
log(diversification$_{i,t}$)	0.327***	0.327***	0.328***	0.368***
	(0.007)	(0.007)	(0.007)	(0.008)
log(relatedness$_{i,t}$)	0.106***	0.106***	0.104***	0.157***
	(0.001)	(0.001)	(0.001)	(0.002)
log(litigiousness$_{k,t}$)	-0.0325***	-0.0451***	-0.0325***	-0.0273*
	(0.012)	(0.012)	(0.012)	(0.015)
opposed$_{i,t}$	0.0275**	0.379***	-0.136***	-0.0404**
	(0.011)	(0.034)	(0.016)	(0.016)
log(litigiousness$_{k,t}$)* opposed$_{k,t}$		0.125***		
		(0.012)		
log(portfoliostock$_{i,t}$)* opposed$_{i,t}$			0.0542***	
			(0.004)	
Observations	4,449,257	4,449,257	4,449,257	1,181,288
LogLikelihood	-2,752,462	-2,752,320	-2,752,426	-1,831,508
Country dummies	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES
Industry dummies	stratified	stratified	stratified	stratified

Note: Coefficients for the hazard of entry are reported. Time period: 2000-2015. Minimum entry year: 1978. Standard errors are clustered on firms and reported in parenthesis.
Legend: *** p<0.01, ** p<0.05, * p<0.1

to patent opposition is positively correlated with entry. Moreover, the positive coefficient of the interaction term displayed in column 2 indicates that, on average, the beneficial effect of being previously opposed is greater in industries characterized by high litigiousness. This evidence suggests that some degree of learning-by-being-opposed, following previous experiences with the procedure, is able to mitigate the negative effect of litigiousness on entry. However, as coefficients of Column 3 suggest, the positive effect of past exposure to opposition varies depending on the size of the firms in terms of portfolio stock, with small firms being disproportionately affected by previous exposure to patent opposition. The hazard of entry due to previous exposure with the opposition procedure decreases by 13% for firms with only one patent. As suggested by the last column, past experience with this EPO's procedure exacerbates the negative effect of the degree of litigiousness of an industry for firms with a smaller portfolio. Small firms seem to be not able to develop the necessary capabilities to face this challenging procedure. The results are confirmed once using as regressor the number of oppositions received prior to entry (see Appendix F).

5.1.3 Heterogeneity across low-tech and high-tech sectors

In interpreting the results of our regressions, one must bear in mind that the effects of IPR regimes on the propensity to enter a TD are also likely to depend upon the nature of innovations themselves. To explore heterogeneity across sectors, we use the OECD's classification (Galindo-Rueda and Verger, 2016) and we aggregate NACE Rev.2 manufacturing industries into low-tech and high-tech domains according to their technological intensity[26]. Descriptive statistics of the two samples, displayed in Table 8, provide clear evidence on the heterogeneity among the two identified group of technologies. First, high-TDs are characterized by a much higher number of yearly applications (*Techopp1*) and greater density of patent thickets compared to low-TDs. Notwithstanding the higher density of network citations among patents, the number of triads is in fact negligible in low-tech industries. As widely recognized in the literature (Hall and Ziedonis, 2001; Dosi, Marengo, et al., 2006), in high-tech industries, products are protected by a much higher number of patents that are often used to block rivals and provide bargaining strength in cross-licensing negotiations, thus creating numerous patent thickets. In these contexts, the density of the network of citations is instead low, because firms exploit sleeping patents and strategic non-use of patents (Torrisi et al., 2016) against competitors. Interestingly, the growth rate of citations to the NPL (*Techopp2*) is greater in low-tech compared to high-tech TDs, on average[27]. Concerning litigiousness through opposition procedures, the rate of opposed patents is greater in low-tech TDs compared to high-tech TDs. As stressed above, this evidence confirms previous findings of a lower firm's incentive to oppose patents in high-tech TDs (Gaessler et al., 2019). In high-tech TDs, where inventions are spread across many patents, patent invalidation does not guarantee freedom to operate in subsequent follow-on innovation. Moreover, firms may prefer patent challenges through court litigation that allow for settlements among parties.

In Table 9 we interact our main indicators of interest with a dummy equal to one for high-tech domains. The results show that previous exposure with the opposition procedure discourages firms from entering new high-tech domains, indicating that firms do not experience any sort of learning by being opposed (Column 1). Moreover, the negative effect of litigiousness (Column 2) and its interaction with the density of patent thickets (Column 3) is particularly strong in high-tech rather than low-tech TDs. Overall, barriers to entry emerging from distortions in patent appropriability conditions are particularly present in high-tech industries characterized by complex technologies.

[26] See Table 3 for the detailed list of high- and low-tech TDs. Our concordance table identifies three additional sectors with respect to traditional manufacturing sectors, namely Civil Engineering (42), Specialised Construction Activities (43) and Computer, Programming and Consultancy (62). We drop these sectors from this additional analysis.

[27] Von Graevenitz et al. (2013), using a similar measure to proxy technological opportunities, found that "technological opportunities in complex technology areas began to decline just after 1992, which coincides with the date at which the growth in patent applications at the EPO picked up".

Table 8: Industry-level variables in low-and high-tech industries, mean values for the period 2000-2015

	Low-tech				High-tech			
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
$\text{techopp1}_{k,t}$	7,883	6,685	51	17,443	27,913	14,628	1,028	51,490
$\text{techopp2}_{k,t}$	0.84	1.10	-0.87	49.23	0.64	0.49	-0.48	2.30
network $\text{density}_{k,t}$	0.08	0.20	0.01	2	0.01	0.01	0	0.13
patent $\text{thickets}_{k,t}$	906	910	0	2,568	18,308	15,968	6	46,861
$\text{litigiousness}_{k,t}$	7.3%	3%	1%	20%	4.7%	2%	1.7%	9.8%

Low- and high-tech TDs classified using the OECD's classification (Galindo-Rueda and Verger, 2016). Values for network density multiplied by 1000.

Table 9: Hazard of entry a new TD and high-tech industries

	1	2	3
$\log(\text{techopp1}_{k,t})$	0.258***	0.243***	0.211***
	(0.031)	(0.031)	(0.031)
$\log(\text{techopp2}_{k,t})$	0.0123***	0.0128***	0.0128***
	(0.002)	(0.002)	(0.002)
$\log(\text{network density}_{k,t})$	0.295***	0.297***	0.305***
	(0.027)	(0.027)	(0.027)
$\log(\text{portfolio stock}_{i,t})$	0.0128*	0.0192***	0.0204***
	(0.007)	(0.007)	(0.007)
$\log(\text{patent thickets}_{k,t})$	-0.0120***	-0.0133***	-0.129***
	(0.003)	(0.003)	(0.014)
$\log(\text{diversification}_{i,t})$	0.329***	0.329***	0.328***
	(0.007)	(0.007)	(0.007)
$\log(\text{relatedness}_{i,t})$	0.106***	0.106***	0.106***
	(0.001)	(0.001)	(0.001)
$\log(\text{litigiousness}_{k,t})$	-0.112***	-0.0607***	-0.142***
	(0.013)	(0.014)	(0.014)
$\log(\text{litigiousness}_{k,t})*$ $\log(\text{portfolio stock}_{i,t})$	0.0505***	0.0575***	0.0579***
	(0.013)	(0.002)	(0.002)
$\text{opposed}_{i,t}$	0.0505***	0.0175	0.0168
	(0.013)	(0.011)	(0.011)
$\text{high-tech}_{k,t}*$ $\text{opposed}_{i,t}$	-0.0602***		
	(0.010)		
$\text{high-tech}_{k,t}*$ $\log(\text{litigiousness}_{k,t})$		-0.212***	
		(0.027)	
$\log(\text{litigiousness}_{k,t})*$ $\log(\text{patent thickets}_{k,t})$			-0.0402***
			(0.005)
$\text{high-tech}_{k,t}*$ $\log(\text{litigiousness}_{k,t})*$ $\log(\text{patent thickets}_{k,t})$			-0.0183***
			(0.004)
Observations	4,449,257	4,449,257	4,449,257
LogLikelihood	-2,752,194	-2,752,170	-2,752,137
Country dummies	YES	YES	YES
Year dummies	YES	YES	YES
Industry dummies	stratified	stratified	stratified

Note: Coefficients for the hazard of entry are reported.
Time period:2000-2015. Minimum entry year: 1978.
Standard errors are clustered on firms and reported in parenthesis.
Legend: *** p<0.01, ** p<0.05, * p<0.1

6 Conclusion

There is increasing concern among scholars that distortions in patent appropriability conditions may play a role in shaping technological competition between firms. Previous studies have documented that complex negotiations over licenses, patent litigation and hold-up potential due to patent thickets may deter technology entry, especially in industries characterized by complex technologies (Lerner, 1995; Cockburn and MacGarvie, 2011; Hall, Graevenitz, et al., 2021). In this paper, we measure patent appropriability distortions using a new measure, namely the frequency of opposition procedures at EPO, which occurs more often than patent litigations, particularly in low-tech TDs.

Our data highlights high rates of opposed patents, suggesting an intense monitoring activity carried out by firms concerning other firms' new patent activity. To what extent the frequency of this procedure represents a barrier to firms' entry into new TD? Our regression analysis suggests that the degree of litigiousness of an industry negatively correlates with the likelihood of a firm entering a new TD. High density of patent thickets also has a discouraging effect on entry, in line with previous results found in the literature (Cockburn and MacGarvie, 2011; Hall, Graevenitz, et al., 2021). On the contrary, technological opportunities encourage firms to enter new TDs, especially when firms hold related capabilities and knowledge. We also document the presence of a learning-by-being-opposed process that mitigates the discouraging effect of TDs litigiousness. However, such a learning process benefits only large firms. Firm's past exposure to opposition procedures negatively affects the decision to diversify in new TDs for small firms.

Exploring sources of heterogeneity across industries, characterized by different degrees of technological intensity, our findings also suggest that distortions in patent appropriability conditions lead to emerging barriers to entry in particular in high-tech TDs. Finally, our results indicate that cost barriers emerging from opposition procedures fall disproportionately on small rather than large firms. This latter finding is particularly worrisome as our work is limited to potential entrants with previous patenting activity at EPO. This sample may indeed underestimate the negative consequences on small non-patenting firms.

This paper contributes to the broad literature on the drivers of a firm's technological entry by assessing the role of a firm's knowledge and capabilities and opportunities stemming from the technological environment. Our empirical evidence indicates that new barriers to entry arising from patent litigiousness and density of patent thickets may be a plausible explanation for the recently observed trend of declining business dynamism. Our work findings justify emerging concerns on whether distortions in patent appropriability conditions may shape technological competition among firms in undesired ways.

Besides the contribution, this paper has some limitations. First, our analysis does not identify causal effects. Rather, our contribution is to document the correlation between technological aspects and a new measure of barrier to entry with TD entry. Second, by aggregating IPC classes in 26 TDs we do not account for heterogeneous aspects within each entry-fields. However, even by conducting the analysis on single IPC classes would not have been without criticisms, since too granular technology classes may not represent distinct entry-fields for firms' diversification attempts. Finally, we note that our unit of analysis is technology entry rather than market entry, the latter being more difficult to capture correctly. Future works will try to add the market dimension to the analysis.

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A Independent Variables - descriptive statistics

Table A1: Descriptive Statistics

	Mean	Std. Dev.	Min	Max
$\log(\text{techopp1}_{k,t})$	7.40	1.76	3.94	10.8
$\text{techopp2}_{k,t}$	-0.030	0.51	-0.87	49.2
$\log(\text{network density}_{k,t})$	-9.68	1.61	-12.8	-6.19
$\log(\text{patent thickets}_{k,t})$	-0.50	1.90	-5.77	2.72
$\log(\text{litigiousness}_{k,t})$	-2.92	0.54	-4.74	0
$\log(\text{portfolio stock}_{i,t})$	2.15	1.38	0	12.2
$\log(\text{diversification}_{i,t})$	0.55	0.61	0	3.22
$\log(\text{relatedness}_{i,t})$	-4.11	1.90	-9.42	0

TD-level and firm-level independent variables in the regression analysis. Log for all variables except the growth rate in NPL refs ($techopp2_{k,t}$).

B Applicants' country of origin

Our new dataset comprised the whole set of patent applicants filling a patent at EPO between 2000 and 2015 in a new TD, where the firm had no previous patenting experience. Table B1 summarized information regarding firm's country of origin, retrieved from the applicant's BVD ID obtained from ORBIS IP. Not surprisingly, most of the EPO's first-time applicants are European (56%) and US (24%) firms. Less than 10% of the applicants are set in Asian countries such as Japan (4,7%), South Korea (2%) and China (2%). The residual category accounts for 11% of our firms. In all our regressions, we therefore include dummies for the firm's country of origin, categorized as in Table B1.

Table B1: Patent applicants' country of origin

country	freq.	percent.	cumul.
1 European	2,528,526	56.03	56.03
2 US	1,089,374	24.14	80.18
3 China	91,078	2.02	82.19
4 Japan	211,874	4.70	86.89
5 South Korea	96,070	2.13	89.02
6 Other countries	495,508	10.98	100.00

Info retrieved from firms' BVD IDs.
Data source: Orbis IP

In Table B2 we show the results of the country-dummies' coefficients included in the baseline regression (Table 5, column 5). It emerges that US and Japanese firms are less likely to entry a TD compared to European firms. On the contrary, firms set in emerging countries such as China and South Korea, have a higher probability to entry.

Table B2: Results of country-dummies' coefficients

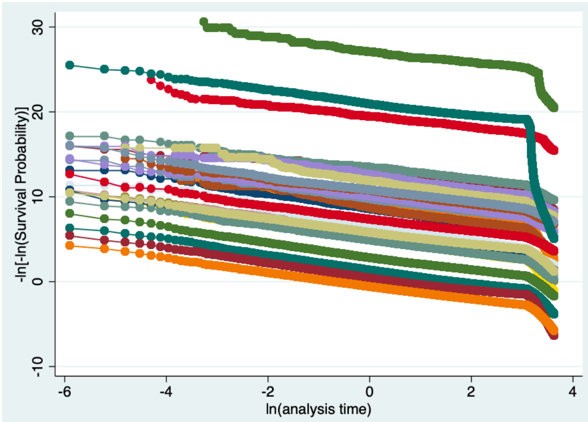
dummies included	results
2.dcountry (US)	-0.888***
	(0.005)
3.dcountry (CHINA)	0.0723***
	(0.028)
4.dcountry (JAPAN)	-0.860***
	(0.006)
5.dcountry (S.KOREA)	0.519***
	(0.032)
6.dcountry (OTHER COUNTRIES)	-0.481***
	(0.008)

Detail about baseline regression's results regarding firm's country-dummies.

C Proportional hazard assumption

The main assumption of the Cox proportional hazards model is proportional hazards. Proportional hazards means that the hazard function of one unit observation is proportional to the hazard function of the other observations, i.e. the hazard ratio is constant over time. We assess the validity of the assumption by plotting estimated $log(-log(survival))$ versus survival time for different TDs, following the TD-stratification. We would see parallel curves if the hazards are proportional. Figure C1 shows

Figure C1: Estimated log(-log(survival)) versus survival time for the 26 manufacturing classes



that the assumption is indeed not violated. We additionally test the proportional hazards assumption through Schoenfeld residuals (Schoenfeld, 1982). The null hypothesis is that the correlation between the Schoenfeld residuals and the ranked survival time is zero. Figure C2 and Figure C3 show that the proportional hazard assumption is not violated for our main variables of interest [28].

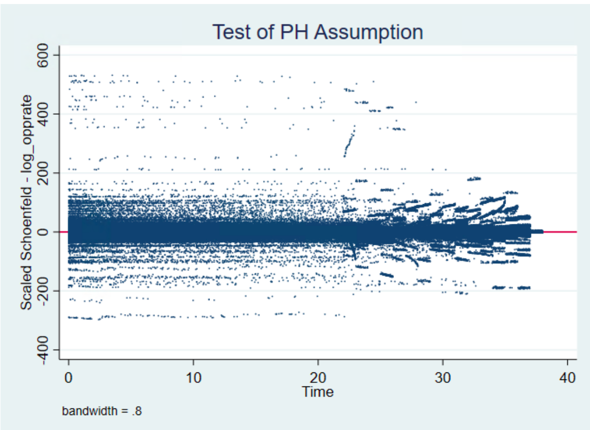


Figure C2: Schoenfeld residuals log(litigiousness)

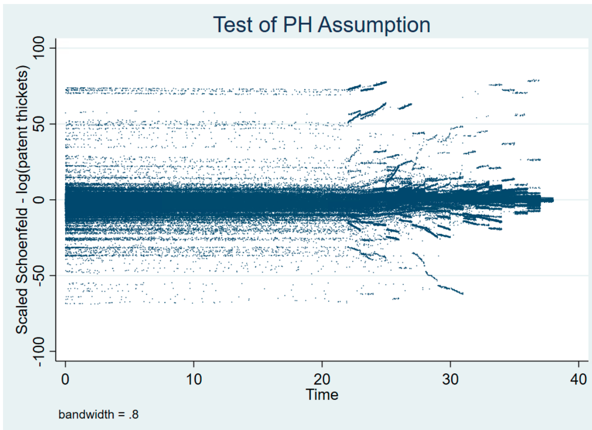


Figure C3: Schoenfeld residuals log(patent thickets)

[28]Similar figures are found for the other variables but are not shown here.

D Other survival models

In this section we compare the semi-parametric Cox estimates with the results of other parametric models, namely the Weibull, the Exponential and the Gompertz.

Proportional hazards models are written

$$h(X_i, t) = h(t)exp(X_i, \beta) \tag{2}$$

In the Cox model, $h(t)$ is left unparameterized. On the contrary, in the parametric approach, a functional form for $h(t)$ is specified. In particular, if we assume $h(t) = exp(a)$ for some a, we have the exponential model, in which the baseline hazard is assumed constant over time. If instead we assume $h(t) = pt^{p-1}exp(a)$, we have the Weibull model with two ancillary parameters, a and p. Finally, by assuming $h(t) = exp(a)exp(\gamma t)$ we obtain the Gompertz model with ancillary parameters a and γ. By allowing ancillary parameters p and γ to vary freely across the industrial sectors through the stratification, we let the shape of the hazard function to be different for different industries, while retaining the proportionality assumption. It is straightforward that, in the latter two models, once we find $\gamma = 0$ or $p = 1$ we are back to the exponential model[29]. Results using parametric models are displayed in Table D1. Across different models, our results are confirmed.

Table D1: Hazard of entry a new TD compared to other survival models

	1	2	3	4
	Cox	Weibull	Exponential	Gompertz
log(techopp1$_{k,t}$)	0.253***	0.0770***	0.0432***	0.100***
	(0.031)	(0.019)	(0.016)	(0.023)
log(techopp2$_{k,t}$)	0.0121***	0.00440	0.0113***	0.0105***
	(0.002)	(0.003)	(0.002)	(0.003)
log(network density$_{k,t}$)	0.295***	0.185***	0.126***	0.273***
	(0.027)	(0.015)	(0.012)	(0.019)
log(portfolio stock$_{i,t}$)	-0.143***	-0.141***	-0.132***	-0.146***
	(0.003)	(0.002)	(0.002)	(0.003)
log(patent thickets$_{k,t}$)	-0.0122***	-0.0127***	-0.00733***	-0.0196***
	(0.003)	(0.003)	(0.003)	(0.003)
log(diversification$_{i,t}$)	0.327***	0.362***	0.368***	0.350***
	(0.007)	(0.006)	(0.006)	(0.007)
log(relatedness$_{i,t}$)	0.106***	0.118***	0.119***	0.116***
	(0.001)	(0.001)	(0.001)	(0.001)
log(litigiousness$_{k,t}$)	-0.0328***	-0.0379***	-0.0246***	-0.0350***
	(0.012)	(0.009)	(0.008)	(0.010)
Observations	4,449,257	4,449,257	4,449,257	4,449,257
LogLikelihood	-2,752,469	-499,658	-525,176	-417,888
Country dummies	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES
Industry dummies	stratified	stratified	stratified	stratified

Note: Coefficients for the hazard of entry are reported. Time period: 2000-2015.
Minimum entry year: 1978.
Standard errors are clustered on firms and reported in parenthesis.
Legend: *** p<0.01, ** p<0.05, * p<0.1

[29]This is our case once we compute the Weibull model ($p = 1.46$) and the Gompertz model ($\gamma = 0.09$) without industry stratification, getting a single value of the ancillary parameters.

E Robustness check: size measured using financial data from ORBIS

Our findings suggest that smaller firms in terms of portfolio stock are affected more by the degree of litigiousness of an industry. In this section we test whether the result is robust to different proxies for firm's size, namely firm's total asset, number of employees and sales. These information are collected through ORBIS but varies substantially across countries (Kalemli-Ozcan et al., 2015), determining a high number of missing values[30]. We therefore use imputation values for missing observations, exploiting other information available at the firm-level (portfolio stock, technological diversification, core field of the firm and year of observation). Information's gaps for these financial variables do not coincide, being possible to have, for a given year, data for one variable and not for the other(s). We exploit this issue by using values of sales and number of employees as additional firm-level data in the imputation algorithm, when available. Moreover, the time span availability of financial variables in ORBIS varies from firm to firm and has a time span of ten years maximum, while our analysis covers the period 2000-2015. We apply the imputation algorithm to fill these additional gaps of information. Results displayed in Table E1 show that smaller firms are disproportionately affected by the degree of litigiousness of an industry, confirming our main results.

[30]Information for these three variables are not available for 37% of our firms.

Table E1: Hazard of entry a new TD and firm's size

	1	2	3	4	5	6
log(techopp1$_{k,t}$)	0.255***	0.254***	0.256***	0.254***	0.256***	0.256***
	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)
log(techopp2$_{k,t}$)	0.0121***	0.0122***	0.0123***	0.0123***	0.0122***	0.0122***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
log(network density$_{k,t}$)	0.294***	0.296***	0.294***	0.296***	0.294***	0.296***
	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)
log(portfolio stock$_{i,t}$)	-0.131***	-0.132***	-0.131***	-0.132***	-0.132***	-0.133***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
log(patent thickets$_{k,t}$)	-0.0124***	-0.0124***	-0.0125***	-0.0126***	-0.0124***	-0.0125***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
log(diversification$_{i,t}$)	0.336***	0.337***	0.338***	0.338***	0.337***	0.337***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
log(relatedness$_{i,t}$)	0.106***	0.106***	0.106***	0.106***	0.106***	0.106***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
log(litigiousness$_{k,t}$)	-0.0319***	-0.170***	-0.0319***	-0.0914***	-0.0320***	-0.148***
	(0.012)	(0.017)	(0.012)	(0.013)	(0.012)	(0.016)
log(total asset$_{i,t}$)	-0.0168***	0.0302***				
	(0.001)	(0.004)				
log(litigiousness$_{k,t}$)* log(total asset$_{i,t}$)		0.0160***				
		(0.001)				
log(employees$_{i,t}$)			-0.0217***	0.0307***		
			(0.001)	(0.004)		
log(litigiousness$_{k,t}$)* log(employees$_{i,t}$)				0.0178***		
				(0.001)		
log(sales$_{i,t}$)					-0.0170***	0.0238***
					(0.001)	(0.003)
log(litigiousness$_{k,t}$)* log(sales$_{i,t}$)						0.0138***
						(0.001)
Observations	4,449,257	4,449,257	4,449,257	4,449,257	4,449,257	4,449,257
Country dummies	YES	YES	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES	YES	YES
Industry dummies	stratified	stratified	stratified	stratified	stratified	stratified

Note: Coefficients for the hazard of entry are reported. Time period: 2000-2015.
Minimum entry year: 1978. Standard errors are clustered on firms and reported in parenthesis.
Legend: *** p<0.01, ** p<0.05, * p<0.1

E.1 Robustness check: learning-by-being-opposed measured using number of oppositions received by the firm in the past

As a robustness check, we exploit additional information about firms' experiences with the EPO opposition procedure. In particular, we count the number of oppositions received by the firm prior to entry in any TD and we add it to our baseline regression (instead of the dummy equal to one if the firm has received at least one opposition in the past). To prevent the loss of observations equal to zero and thus avoiding biased estimates, an extra value of 0.5 was added (e.g. log(nr of oppositions + 0.5) when using the log transformation on these variable. As shown in Table E2, previous results regarding a size-effect on the degree of learning-by-being-opposed are confirmed. The amount of previous experiences with the opposition procedure has a positive but not significant coefficient (Column 1). However, once interacting our alternative variable with portfolio's size, the number of previous oppositions received by the firm is negatively correlated with entry, with portfolio's size positively moderating this effect. Again, the size of the firm matters: smaller firms in terms of patent portfolio are affected more and negatively by past exposure to opposition procedures.

Table E2: Hazard of entry a new TD and opposition experience

	1	2
log(techopp1$_{k,t}$)	0.253***	0.253***
	(0.031)	(0.031)
log(techopp2$_{k,t}$)	0.0120***	0.0121***
	(0.002)	(0.002)
log(network density$_{k,t}$)	0.295***	0.295***
	(0.027)	(0.027)
log(portfolio stock$_{i,t}$)	-0.143***	-0.143***
	(0.003)	(0.003)
log(patent thickets$_{k,t}$)	-0.0122***	-0.0123***
	(0.003)	(0.003)
log(diversification$_{i,t}$)	0.327***	0.327***
	(0.007)	(0.007)
log(relatedness$_{i,t}$)	0.106***	0.106***
	(0.001)	(0.001)
log(litigiousness$_{k,t}$)	-0.0327***	-0.0324***
	(0.012)	(0.012)
log(nr oppositions$_{i,t}$)	0.00749	-0.395***
	(0.012)	(0.042)
log(portfolio stock$_{i,t}$)$*$ log(nr oppositions$_{i,t}$)		0.0555***
		(0.006)
Observations	4,449,257	4,449,257
LogLikelihood	-2,755,540	-2,752,320
Country dummies	YES	YES
Year dummies	YES	YES
Industry dummies	stratified	stratified

Note: Coefficients for the hazard of entry are reported. Time period: 2000-2015. Minimum entry year: 1978. Standard errors are clustered on firms and reported in parenthesis.
Legend: *** p<0.01, ** p<0.05, * p<0.1