Do Patent Assertion Entities Harm Innovation?
Evidence from Patent Transfers in Europe

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Les chasseurs de brevets nuisent-ils à l'innovation ? Une étude sur les transferts de brevets en Europe

Résumé

Au cours des deux dernières décennies, les possibilités accrues de monétisation des brevets ont favorisé l'émergence d'institutions facilitant la vente de brevets.

La présence influente et controversée de nouveaux intermédiaires, tels que les chasseurs de brevets (PAEs), a suscité de nombreux débats, notamment aux U.S., concernant leur implication dans le marché des brevets et dans la dynamique de l'innovation.

Nous contribuons à ce débat en apportant des résultats basés sur l'activité des PAEs en Europe. En nous appuyant sur les transferts de brevets EPO (Office européen des brevets), nous montrons que les PAEs obtiennent des brevets de haute qualité.

Ils peuvent ainsi accroître la liquidité dans le marché des brevets et améliorer son efficacité. Cependant, une fois transférés aux PAEs, les brevets reçoivent significativement moins de citations. Ce dernier résultat suggère que les entreprises productrices, dont les technologies se rapprochent de celles détenues par les PAEs, peuvent anticiper un risque accru d'être poursuivies. En conséquence, elles réduisent leur effort d'innovation dans les domaines peuplés des PAE. Ces résultats sont robustes à différentes mesures de citations et techniques économétriques considérées.

Mots-clés: Marché de brevets; Chasseurs de brevets; Monétisation des brevets; Citations; Innovation

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Abstract

The recent upsurge of patent litigation cases initiated by patent assertion entities (PAEs) in the U.S. has led to an intense debate about their effect on innovation performances and on the IP system functioning. We contribute to this debate by providing original evidence based on the patenting activity of PAEs in Europe, a region where the patent assertion landscape is growing rapidly and the imminent introduction of the Unified Patent Court and the Unitary Patent will upset the current schemes. Relying on EPO (European Patent Office) data on patent transfers and patent citations, our results show that PAEs acquire patents with high average technological quality. They may thus increase liquidity in the patent market and enhance its efficiency. However, after a transfer occurs, patents transferred to PAEs receive significantly fewer citations. This suggests that producing companies whose business makes their technologies close to the ones acquired by PAEs may perceive an augmented risk of being sued. As a consequence, they reduce their innovative effort in fields populated by PAEs and this reflects into lower citations flowing towards PAEs' acquired patents. These results are robust to different measures of citations considered and to different econometric techniques.

Keywords: Market for technology; Patent assertion entities; Patent trolls; Patent intermediaries; Patent citations; Innovation.

JEL: O31; O34

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1 Introduction[1]

Once seen merely as a means of protecting an invention, patents are now considered as marketable assets that can be acquired, held, licensed and sold strategically (Papst, 2012). Markets for technology have expanded rapidly in the last 20 years or so. According to Ocean Tomo (Elsten and Hill, 2017), in 2015 intangible assets (mainly patents, software, trademarks and copyrights) represented 84% of the S&P 500 market capitalization – corresponding to 16% of growth from 1995 – and 71% of that of the S&P Europe 350.

Due to increased opportunities for patent monetization, the activity of companies that facilitate the transfer of exclusive rights to inventions has recently experienced a tremendous upsurge (Hagiu and Yoffie, 2013). Consequently, new intermediaries such as patent aggregators and patent assertion entities (PAEs) have become quite influential and controversial, especially in the ICT industry. Recent studies have estimated that the PAE business in the U.S. is worth around $30 billion in settlements and licensing fees annually (Carter, 2013; Yeh, 2013).

So far, the PAE phenomenon and the related scholarly literature have been largely US-centred. Over the past decade, the U.S. patent system has indeed experienced an explosion of litigation cases initiated by PAEs.[2] Not surprisingly, a heated debate has intensified on the economic role that these companies play in the market for patents and on their impact on innovation activities.

A politically diffused opinion is that patent trolling[3] is becoming a growing concern (Cohen et al., 2016; Lemley and Feldman, 2016) or even the *"most significant problem facing the patent system today"* (Lemley, 2006, p. 2). Indeed, in reaction to the proliferation of patent lawsuits initiated by PAEs, the U.S. Congress recently introduced several bills proposing to finely regulate the process of patent licensing and assertion. Moreover, the new inter partes reviews implemented by the 2011 American Invent Act and a number of subsequent U.S. Supreme Court decisions over issues such as patentable subject matter, attorney fees and forum shopping have been directed to curtail the PAEs' activity (Fusco, 2016).

Conversely, the analysis of the European realm has remained on the sidelines so far and only a few recent papers have explicitly addressed the question of PAEs in Europe (Fusco, 2013; Thumm and Gabison, 2016; Thumm, 2018). In light of recent developments, this is not entirely justified. While it is true that patent monetization is relatively less often pursued in Europe compared to the U.S., due to a combination of fragmentation of intellectual property jurisdictions and smaller damages awards (Mayergoyz, 2009), PAEs nonetheless are more and more active in the European patent market. Recently, Interdigital, a U.S. wireless technology firm specialized in generating revenues by licensing and asserting patents, acquired the patent licensing business of Technicolor, a French media and entertainment company, in a deal valuing the unit at $475 million. Moreover, PAEs also increasingly account for a substantial and largely unrecognized share of patent litigation

[1]All our thanks to Stefania Fusco, Fabian Gäßler, Francesco Lissoni, Catalina Martinez, Pierpaolo Parrotta, Julien Penin, Gianluca Tarasconi, Marco Vivarelli, Georg von Graevenitz and to participants in the: 2017 VIII IBEO Workshop in Corte (FR), Cournot seminar at Beta in Strasbourg (FR), EPIP2017 conference in Bordeaux (FR), Via Inno Seminar in Bordeaux (FR), RITM seminar at Paris Sud (FR). We would also like to thank the ANR for its financial support (NPEIE Project, no. ANR-17-CE26-0014-01).

[2]In 2016, about 67% of all U.S. patent lawsuits were filed by non-practicing entities (the large majority represented by PAEs), up from the 61% experienced in 2015 (2015 Patent Dispute Report, Unified Patents; figures available at `https://www.unifiedpatents.com/news/2016/5/30/2015-patent-dispute-report`)

[3]PAEs are sometimes called, in derogatory terms, "patent trolls". Credit for coining the term "patent troll" is given to Peter Detkinn, former Assistant General Counsel for Intel, who started using the term after being sued for defamation for defining an opposing party as "patent extortionists" (Sandburg, 2001).

cases in Europe (Fusco, 2013; Ortiz, 2016). Indeed, recent figures demonstrate that their presence in European courts is not negligible. Darts-IP (2018) shows that, during the period 2007-2016, PAE-related litigation cases in Europe grew about 19% year to year. In this regard, it is not surprising that a coalition of companies (IP2Innovate) including Adidas, Daimler, Intel, Google, SAP and Spotify has recently urged the European Commission (Reuters, Apr 5, 2017)[4] to take action against the explosion of lawsuits brought in Europe by PAEs and has promoted initiatives and debates at the European Parliament.[5]

Thumm (2018) provides an in-depth discussion of the main reasons why the PAEs' activity has recently increased its focus on the European market. On the one hand, recent patent reforms, and in particular the 2011 America Invents Act, reduced the opportunities of asset monetization for PAEs in the US. At the same time, several recent U.S. court decisions have set legal precedents that both limit the likelihood of obtaining an injunction and make it harder to acquire and assert software-related patents. Conversely, EU institutional and legal changes and the imminent introduction of the Unified Patent Court (UPC) and the Unitary Patent (UP) are making the European patent monetization landscape potentially more attractive for PAEs.

To the best of our knowledge, almost all existing quantitative studies on PAEs and innovation refer to the U.S. context.[6] Moreover, with the exception of Fischer and Henkel (2012), they focus on patent litigation data. The extant evidence thus largely leaves out of the analysis enforcement activities settled out of court, i.e. those that did not become public. Therefore, figures based exclusively on patent litigation give a partial intuition of the magnitude of trolling activities in the market for technology, together with their implications, as *"these visible actions are just the tip of the iceberg"* (Shapiro and Scott-Morton, 2014, p. 469). Indeed, instead of going through litigation, PAEs are more likely to prefer to set royalty demands strategically below litigation costs in order to make the business decision to settle an obvious one (Leslie, 2008). This behavior makes it difficult to trace their business and to properly analyze their impact. In all, data only based on patent litigations underestimate the presence of PAEs in the market for patents.

We partially contribute to filling this gap by building a unique database of PAEs' patenting history at the European Patent Office (EPO). This allows for a wider and more systematic identification and analysis of the activity of PAEs in Europe, overcoming part of the limitations related to patent litigation data.

The aim of the paper is to provide a deeper understanding of the underground phenomenon of PAEs' business and, importantly, of its impact on innovation activities and knowledge diffusion from a wider perspective. To do so, we look at the pattern of citations received by the patents they buy. The idea is that (forward) citations are a measure of the cumulative impact of research and an indicator of the use of the protected technology by innovating and producing companies. Our approach is to compare the pattern of citations received by PAE-acquired patents, before and after the transfer, with the pattern of citations received by patents either acquired by practicing entities (PEs) or that are never transferred. Overall, our approach employs a triple difference estimator to evaluate the impact of PAEs on the use and diffusion of technological knowledge.

Results show that patents acquired by PAEs are, on average, of high technological quality. Before a transfer takes place, they indeed receive a substantially higher number of citations compared to

[4] `https://uk.reuters.com/article/europe-patents-idUSL2N1HD25D`

[5] `http://ip2innovate.eu/events/`

[6] See for example, Lerner (2006); Reitzig et al. (2010); Risch (2012); Fusco (2013); Love (2013); Cohen et al. (2014, 2017).

patents that have never been transferred, and similar to patents that have been transferred to PEs. However, after the transfer occurs, we find a strong decline in the number of citations received by patents acquired by PAEs: patents transferred to PAEs receive around 6% fewer citations per year than patents transferred to PEs. These results are robust to different samples and to diverse econometric specifications.

The paper is organized as follows. In Section 2 we introduce our main hypotheses about the impact of PAEs on innovation and technology diffusion. We present data and key figures on the presence of PAEs at the European Patent Office in Section 3. The empirical strategy and the main variables are described in Section 4. Section 5 presents the results. Section 6 concludes.

2 Background and principal hypotheses

How do PAEs affect innovation? The rise of litigation cases initiated by PAEs has sparked a debate regarding their value and impact on innovation. The main point of contention is whether patent enforcement pursued by these entities is an efficient mechanism for technology transfer and the creation of new products, or whether it is simply a means of collecting money for avoiding litigation (constituting a hidden cost for innovators, thus reducing incentives to perform R&D). The answer matters not just for the debate over the desirability of the existence of PAEs but, pragmatically, for guaranteeing long-run rates of technological diffusion and the efficiency of the patent system altogether.

Advocates of PAEs argue that such entities, by acting as intermediary organizations, reduce matching costs, help enforcing patent rights and inject liquidity in the patent market, therefore positively contributing to the efficiency of the secondary market for inventions.

Due to the fact that a threat of legal action is sufficient to receive damages or settlement payments, regardless of actual patent infringements, opponents of PAEs argue instead that these entities simply exploit imperfections in the market for patents, extracting rents from producing and innovating firms.

2.1 PAEs as market-makers

In the patent market, technology suppliers and buyers potentially interested in developing a particular technology meet several times to transfer rights, through either sales or cross-licenses. In most of the cases, bilateral transactions are privately negotiated and involve interested hundreds or thousands of patents at once.[7] Outside of bilateral deals, patent buyers and sellers frequently have difficulty finding each other, since searching for and identifying potential partners require considerable time, effort and competences (Hagiu and Yoffie, 2013). The patent market is indeed characterized by information asymmetries on both sides: due to the embryonic nature of innovation processes, knowledge suppliers have better knowledge of the intrinsic value and characteristics of their inventions; conversely, buying companies can better evaluate the commercial value of those inventions. Likewise, the technological value of an invention is subject to strong complementarities and portfolio effects (Parchomovsky and Wagner, 2005; Gans and Stern, 2010). Therefore, patent intermediaries such as PAEs may serve to connect inventors with entities that may create products

[7]For example, in December 2012, Kodak sold more than one thousand digital imaging patents to a consortium of companies (among them, Apple, Google, Facebook and Samsung) in a deal valuing the transfer at $525 million.

from the inventions (Khan, 2013). In turn, they may strengthen the demand within IP markets by offering a viable "exit" for innovators who are looking for ways to extract value from patents by means other than practicing (Papst, 2012).

Moreover, the asymmetry in financial resources between small inventors and large patent holders or manufacturers prevents the former from making a credible threat to litigate against possible infringements (Haber and Werfel, 2015). This is due to the high costs associated with litigations[8] (especially in cases of defeat in court) and to a lack of resources, time and know-how, on the inventor's side.[9]

The combination of high search costs and financial constraints paves the way, in principle, to intermediaries between inventors, investors and technology users, thereby providing the opportunity to economize on the costs of expertise to identify and sell profitable inventions (Lizzeri, 1999; Hoppe and Ozdenoren, 2005). According to this view, PAEs may improve the efficiency of the market for technologies, indirectly spurring innovation. PAEs may thus act as intermediaries that identify undervalued patents and invest time and resources to find other firms interested in those patents (McDonough, 2006). Following Shrestha (2010), we call this hypothesis the "Market-makers hypothesis".[10]

H1. Market-makers hypothesis *PAEs provide inventors with competences, capital, and bargaining power, increasing the efficiency of the market for technology and, in turn, facilitating the creation and diffusion of technological knowledge.*

2.2 PAEs as market-breakers

A conflicting hypothesis suggests instead that the main business of PAEs is to extract rents from productive and innovative firms. These rents originate from the inefficiency of the legal patent system (Burk and Lemley, 2009; Feldman, 2012), where a threat of legal action is sufficient to induce targeted firms to settle, regardless of the actual patent infringement (Lemley and Shapiro, 2006). Whenever a patent holder can obtain an injunction that will force the downstream producer to take the product off the market, the threat can be very effective.

This is particularly true for complex technologies, and in general all inventions in the information technology sector in which possibly many patents are associated with a single product, and when manufacturers have already invested irreversible technology-specific capital (Lemley and Shapiro, 2006). Since PAEs do not depend on the final product market, conventional market remedies, such as cross licenses, are ineffective in preventing PAEs from pursuing holdup strategies (Lu, 2012).

In order to extract high licensing fees, PAEs may use weak patents to engage in frivolous litigation (Lu, 2012; Feng and Jaravel, 2016). Importantly, they often impose litigation and licensing costs that are disproportionate to the value of the patented technology, thereby creating an unwanted

[8] According to Lanjouw and Schankerman (2004), small patentees are relatively disadvantaged in enforcing their IPRs and thus more likely to litigate than negotiate.

[9] For example, France Brevets, the sovereign patent fund established by the French government, has the mission of monetizing patent portfolios of small and medium French companies and public research centers. In 2011 France Brevets signed an agreement with Inside Secure, a French company specialized in secure transactions, for the exclusive license of 70 NFC (near field communication) patents. Two years later, France Brevets filed patent infringement lawsuits against HTC and LG in the U.S. and in Germany for using two patents (US 6700551; US 7665664) that were granted to Inside Secure in 2004 and 2010. LG decided to settle in 2014, while HTC did not settle and lost the case in 2015.

[10] Other scholars use the term "middleman hypothesis" (Lemley and Feldman, 2016).

"tax" on innovative products and services (Feldman and Frondorf, 2015). In this situation, PAEs may negatively impact innovation activities, indirectly. Firms operating in technologies in which PAEs have acquired patents may indeed interrupt their R&D investments and shift focus in order to avoid future litigations.[11]

As different and largely conflicting to the *Market-makers* hypothesis, we can thus formulate the following hypothesis:

H2. Market-breakers hypothesis *PAEs create an obstacle to innovation activities by imposing a "tax" on producing and innovating companies operating in the fields they are active in.*

2.3 Main evidence

Theoretical studies reveal potential negative impacts of PAEs on innovation dynamics (Lemley and Shapiro, 2006; Reitzig et al., 2007; Turner, 2011; Penin, 2012). This is coherent with anecdotal evidence (Cohen et al., 2016). However, empirical evidence about the consequences of PAEs on innovation is rather inconclusive. Importantly, the extant literature has mainly studied the direct impact of PAEs on targeted firms in terms of additional licensing and extra litigation costs to sustain, while the indirect consequences on the market for innovation, taken as a whole, have not been deeply studied.

A second shortcoming of the extant evidence is that it is mainly based on patent litigation data. In particular, data on patent litigations have been used by a number of legal scholars and economists mainly to (1) find evidence of "opportunistic" behavior of PAEs and to (2) evaluate the impact of litigations on R&D investments and sales of innovating companies targeted by PAEs.

With regard to the first point, results are mixed. Some authors suggest that PAEs behave opportunistically. Feldman and Frondorf (2015) surveyed the in-house legal staff of 50 product companies characterized by initial public offerings (IPOs) between 2007 and 2012. They found that 40% of respondents received patent demands during the time of their IPOs, with those demands coming mainly from PAEs. Cohen et al. (2014) found that cash availability is the principal determinant of PAEs' litigation targeting, while this is not true for small inventors and producing companies. Love (2013) found that PAEs litigate their patents late in the patent life, waiting until a lucrative industry has developed before filing suit. Feng and Jaravel (2016) found that PAEs purchase more patents that are "more obvious and contain vaguer claims", suggesting that they acquire patents with the sole purpose of litigation.

While it is true that PAEs target successful commercializers and cash-rich firms, this does not imply that their litigations are as "frivolous" as suggested by the anecdotal evidence. Indeed, recent works found that PAEs are not (mainly) involved in frivolous litigations and, interestingly, they do not seem to assert low-quality patents. As selected examples, Shrestha (2010) compared a sample of patents litigated by 51 PAEs to a sample of patents litigated by other entities, finding that the former were of higher quality (i.e. more cited and with a wider technical breadth). Risch (2012) analyzed the patents asserted by the ten most-litigious PAEs in the U.S. and found them to be qualitatively similar to those asserted by producing companies. Similarly, focusing on patents acquired (instead of

[11] This explains the increasing importance of defensive patent aggregators, such as RPX and AST, which purchase patents to mitigate the risk and the cost of litigation in order to offer an insurance against patent troll risk to inventors and producing companies (Papst, 2012; Hagiu and Yoffie, 2013).

patents litigated) by PAEs, Fischer and Henkel (2012) found evidence suggesting that PAEs acquire patents of high technological quality.

With regard to the second point, the extant literature substantially agrees that the (litigation and licensing) costs to targeted firms are high and that reductions in R&D and other investments are relevant (Cohen et al., 2014). For example, Tucker (2014) examined a case study on how the actions of Acacia Research Corporation, a well-known PAE,[12] have affected technology sales of U.S. firms in the field of medical imaging technology. She found that sales of products protected by patents affected by litigation with Acacia have considerably diminished as a consequence of a reduction in incremental product innovation during the period of litigation. Bessen et al. (2011), analyzing the defendant's stock market events around the filing of patent lawsuits involving a PAE over the period 1990-2010, found that these lawsuits were associated with half a trillion dollars of lost wealth to defendants. Finally, Bessen and Meurer (2013) estimated the direct costs of defendants in litigations with PAEs at about $29 billion in 2011. However, Schwartz and Kesan (2013) contested the analysis proposed by Bessen and Meurer (2013), arguing that their results are not based on a random or representative sample. Therefore, the $29 billion cost estimated by Bessen and Meurer (2013) should be viewed as the "highest possible limit".

If PAEs do impose high costs on the targeted firms, it is however possible that they serve as tax collectors for inventors from whom patents have been bought. Payments from innovative companies might not be considered as a reduction in R&D efforts if they are counterbalanced by significant transfers to the original inventors. However, early evidence is not encouraging. Bessen and Meurer (2013) used survey evidence on U.S. companies and found that payments to independent inventors only account for 5% of the direct costs that defendants incur in litigation with PAEs, while 62% goes to PAEs' operating costs (including 15% which goes to payments to the NPEs' own R&D departments), 23% to legal expenses, and 10% to profits.

3 Data

To build the database of patents owned by PAEs at the EPO (the PAE-EPO database), we first produce an extensive (though not exhaustive) list of PAEs active in the European technology market. We do so by exploiting several external sources of information about PAEs that are active worldwide. Then we match the PAE list with the list of applicants retrieved from the EP-Register database to track their patenting history at the EPO.

3.1 Database construction

The PAE list We broadly define PAEs as independent organizations (legal entities) which own or purchase patents filed from or granted to other companies or individual inventors without the intent of developing, producing and/or commercializing the related products or processes. In most cases, these firms do not conduct any R&D activity. Their main business consists in generating revenues by asserting acquired patents against alleged infringers (Chien, 2008). This definition excludes certain inventors that are often considered as non-practicing entities, in particular individual inventors, universities and academic institutions who initiate suits.

[12] Quinn (2010) labeled Acacia as the "mother of all patent trolls".

To individuate active PAEs, the majority of existing related studies exploit information contained in patent litigation data. As a primary source of data we thus follow the same approach, looking at litigations that occurred in Germany, the UK and the US. First, we select all the PAEs' names collected by Love et al. (2017) for Germany and the UK.[13] Data on patent litigations in Germany cover the period 2000-2008. With respect to the UK, we extend the list provided by the same authors, which originally covers the period from 2000 to 2013, by looking at litigations that occurred in 2014 and 2015. Precisely, within the list of names recorded in the UK Patent Court Diary during 2014 and 2015,[14] we manually extract new emerging PAEs using punctual web information, and add them to the existent list. Finally, we also consider active PAEs involved in patent litigations in the US. For this information we rely on Cotropia et al. (2014) who report PAEs involved in patent litigations in the U.S. from 2010 to 2012.[15]

We then complement the list of PAEs by collecting information from web sites specialized in monitoring the PAE activity. 25 PAEs active in the European market for patents are retrieved from PatentFreedom, a for-profit organization that gathers and analyzes data about PAE activities.[16] A second source of data comes from IP-Checkups, a web resource that extensively collects names of active non-practicing entities worldwide. Precisely, IP-Checkups provides a partial list of eleven PAEs, together with a comprehensive list of related subsidiaries.[17]

By making use of these diverse sources, we end up with a final list of PAEs potentially active at EPO, composed of 321 unique entities.[18] After applying the matching procedure described below, we have been able to identify 110 entities effectively operating in the European market for patents (i.e. owning at least one EP application).

The European Patent Register To build a unique database of European patents owned by PAEs we rely on information provided by the European Patent Register (EPR, November 2015). The EPR contains all the publicly available bibliographic, procedural and legal status information on European patent applications as they pass through each stage of the granting process. More precisely, as highlighted by the European patent system documentation: "Up to grant of the European patent, transfers, licenses and other rights in respect of European patent applications are registered centrally in the European Patent Register in accordance with Rules 22 to 24 EPC. After grant of the European patent, a transfer is registered in the European Patent Register only during the opposition period or during opposition proceedings, in accordance with Rule 85 in conjunction with Rule 22 EPC".[19]

This allows us to reconstruct the patent ownership histories during the entire granting process and thus to identify potential patent transfers within this period, which is crucial for analyzing the

[13] Love et al. (2017) define 7 groups of potentially non-practicing entities: (1) IP Licensing Co., Acquired Patents; (2) IP Licensing Co., Owned by Inventor or Failed Product-Producing Co.; (3) University, University IP Licensing Spin-off, or Other Research Institution; (4) Start-up, Suing Pre-Product; (5) Individual; (6) Industry Consortium; (7) IP Subsidiary of a Product-Producing Co. For the purpose of our study, we only extract information contained in groups (1) and (2).

[14] http://www.justice.gov.uk/courts/court-lists/list-patents-court-diary

[15] The authors classify all patent holders into one and only one of the following groups: (1) University; (2) Individual Inventor; (3) Large Patent Aggregator; (4) Failed Operating or Start-up Company; (5) Patent Holding Company; (6) Operating Company; (7) IP Holding Company Owned by Operating Company; and (8) Technology Development Company. For the purpose of our study, we only extract information contained in groups (3) and (5).

[16] The names of PAEs are reported by Fusco (2013).

[17] http://www.ipcheckups.com/npe-tracker/npe-tracker-list/

[18] Most of them are subsidiaries or ad-hoc companies that appear to have been formed solely to hold and enforce a patent or a small portfolio of patents.

[19] https://www.epo.org/law-practice/legal-texts/html/natlaw/en/ix/index.htm

role of patent intermediaries such as PAEs.[20]

As stressed by Ciaramella et al. (2017), the distribution of legal events (i.e. change of ownership, change of applicant name or address, patent licensing, etc.) in European national patent offices is dominated by registrations appearing at the EPO (almost 75% of all legal events). Most of the EPO events (80%) concern EPO applications that were still under examination, more precisely around the grant date. This evidence makes the use of the EPR data very suitable for our study.

A change in applicant information registered in the database reveals a potential patent transfer.[21] However, as discussed by De Rassenfosse et al. (2017), there are at least two shortcomings that should be considered when analyzing patent transfers: i) not all changes are communicated to the EPO (thus there exist non-observable patent transfers); ii) not all communicated changes correspond to genuine transactions (just part of the registered changes should be considered as effective transactions).

The first shortcoming cannot be addressed by relying exclusively on the EP Register. However, it should represent a minor issue. In fact, as discussed in Ciaramella et al. (2017), even if registration of patent transfers is not mandatory, the lack of registration may have consequences for third parties acting in good faith, notably subsequent purchasers. In addition, strong incentives to declare a transfer are indeed present in almost all the European legislations. They affect IPR enforcement rights against third parties (this is the case, for example, of Spain and Italy), or the claiming of costs and expenses in proceedings during the period from the effective transfer and the registration (this is the case for the UK). Furthermore, in some countries (such as France) contracts related to patent transfer can be enforceable against third parties only if they have been registered, which implies that "infringement damages cannot be obtained for the period after the contract but prior to the registration" (Ciaramella et al., 2017). As for Germany, Gäßler (2016) stresses that the new holder of an IP right gains legitimacy to interact with the patent office and the courts only after formally declaring the transfer. Finally, looking at some statistics provided by FTC (2016), PAEs declare about 95% of their acquisitions of USPTO patents. Of those, 70% were recorded within 90 days from the date of the declared acquisition and 82% within one year.

The second shortcoming can be addressed by data cleaning and harmonization. EPR might register a patent transaction when in fact the event simply concerns a change in the firm name, given that names and addresses of the parties listed in the EPR database have not been harmonized or disambiguated. The very same applicant may thus have several customer identifiers, again leading to false positives in the analysis of patent transfers. To overcome this last issue, we harmonize and standardize applicant names following a procedure described in the Appendix A-1.

Due to the relatively recent explosion of the PAE business, we restrict our analysis to EP patents filed during the period 1997-2010 (1,657,189 patent applications).[22] After applying the name cleaning and standardizing procedure described below and in the Appendix A-1, we individuate 288,541 unique patent applicants registered at EPO from 1997 to 2010. The total number of transferred

[20] Precisely, we exploit information contained in the PATSTAT Register table 'REG107_PARTIES' – which provides data on applicants, inventors and legal representatives – to track changes of parties over time during the granting process. The types of parties are distinguished by the attribute 'TYPE'. For our purposes, we only consider applicants and inventors recorded, respectively, as 'A' and 'I'.

[21] To capture possible patent transfers we exploit information contained in the field 'REG107_PARTIES.CUSTOMER_ID'.

[22] We decide to exclude patents filed after 2010 to ensure that there is sufficient time to observe both patent citations and transfers.

patents is 284,337, representing 17.16% of the total sample.[23] Within them, patents that are traded only once in their EPO life cycle come to 254,848 (89.63% of cases), those traded twice represent 9.37% of cases (26,637 patents) and more than twice 1% of cases (2,852 patents). For the purpose of our study, we focus our attention only on first transfers.[24] Table 1 provides an overview of the phenomenon.

Table 1: Number of patent transfers registered at the EPR

Number of transfers	Freq.	Percent	Cum.
0	1,372,852	82.84	82.84
1	254,848	15.38	98.22
2	26,637	1.61	99.83
3	2,644	0.16	99.99
4	189	0.01	100.00
5	19	0.00	100.00

Years of patent filing: 1997-2010. Results obtained after cleaning and standardizing applicant's name and address. For the methodology description, see the Appendix A-1.

The PAE-EPO database To identify EP applications assigned to PAEs, we perform two separated semantic matching procedures between entity names included in the aforementioned PAE list and the cleaned applicant names recorded in the EP-Register database[25].

The first procedure is based on an exact string matching, leading to the identification of 3,591 patents. The second procedure is a probabilistic matching which allows for a minimum amount of discrepancy between the applicant and PAE names to be matched. For the matching, we apply the RECLINK Stata algorithm (Blasnik, 2007).[26] This latter matching method leads to the identification of 3,942 EP patents in which at least one PAE appears as owner in the patent history, representing 0.24% of the entire basket of EP applications filed from 1997 to 2010 at the EPO (1,657,189 patent applications at EPO).[27] Table 2 lists the top 10 PAEs in terms of EP patents owned.

[23]It must be stressed that, even after cleaning and standardizing applicant names, we are not able to exclude systematic "intragroup" patent transfers from our final sample if names are not similar. As highlighted by Ciaramella et al. (2017), more than 30% of EPO patents in all fields change ownership at least once. Looking at the share of transfers per technological sector, they find that ICT-related fields are abundantly above the average, with more than 35% transfers individuated. For the field of medical technologies, they exploit additional information on corporate structures to further distinguish between "intragroup" and "bare" changes of ownership. Their results indicate that, in the medical domain, more than two-thirds of transfers are "intragroup", that is, between related corporate entities. Given these numbers, even if we significantly reduce the number of "raw" transfers in the ICT domain, we are aware that "intragroup" transfers are not fully individuated by applying our methodology.

[24]To assess the robustness of the results presented in Section 5 we exclude from our analysis patents transferred more than once during their life-cycle at EPO. Results are robust and are available upon request by the authors.

[25]To perform semantic matches we rely on cleaned applicant names derived from steps 1 and 2 described in the Appendix A-1

[26]RECLINK employs a modified bigram string comparator and allows user-specified match and non-match weights. We set the algorithm score at 0.95. This threshold has been chosen by visually comparing applicant names with PAEs names on a random sub-sample of 100 cases. For robustness checks we applied different thresholds (0.90 and 0.99): results do not change significantly and are available upon request by the authors.

[27]Individuated PAEs active at EPO in the period 1997-2010 come to 110 (0.04% of the total number of registered applicants).

Table 2: Top 10 PAEs per EP patents owned (1997-2010)

PAEs	Freq.	Percent	Cum.
INTERDIGITAL	1579	25.57	25.57
MOSAID TECHNOLOGIES	337	5.46	31.03
INTELLECTUAL VENTURES	293	4.75	35.78
UNITED VIDEO PROPERTIES	275	4.45	40.23
RAMBUS	244	3.95	44.18
ROCKSTAR	194	3.14	47.32
IPCOM	115	1.86	49.18
TESSERA	109	1.77	50.95
IPG HEALTHCARE ELECTRONICS	95	1.54	52.49
WI LAN	76	1.23	53.72

Years of patent filing: 1997-2010. Results obtained after cleaning and standardizing applicant's name and address and applying the probabilistic matching. For the description of the methodology applied, see the Appendix A-1.

3.2 PAE activity at EPO: key figures

The industry PAEs essentially operate in ICT industries and, in general, in all the "complex" technologies (Kingston, 2001), in which a new product or process is composed of numerous separately patentable elements, leading to the fragmentation of the relevant IP ownership. This is confirmed by our data where, according to the 35-class OST patent classification (Schmoch, 2008),[28] the four most representative technological fields in which PAEs operate are Digital Communication (45%), Telecommunications (18%), Computer Technology (12%) and Audio and Visual Technology (9%) (See Figure 1). For this reason, from now on we restrict our analysis to high-tech patents only, as defined by the Eurostat classification.[29]

PAE high-tech patent applications come to 3,082, which represents 78% of all PAE patent applications. However, if historically PAEs have been active mainly only in the high-tech sector, in the second half of the 2000s PAEs started a process of business differentiation and entered new markets,[30] in part because low-tech industries have increased their use of computer-based technologies and in part because more low-tech companies started to sell patents to monetize their investment in R&D. This trend clearly emerges from Figure 2 that shows the number of patent applications with at least one PAE as patent owner by year of filing and by sector (high-tech and low-tech).

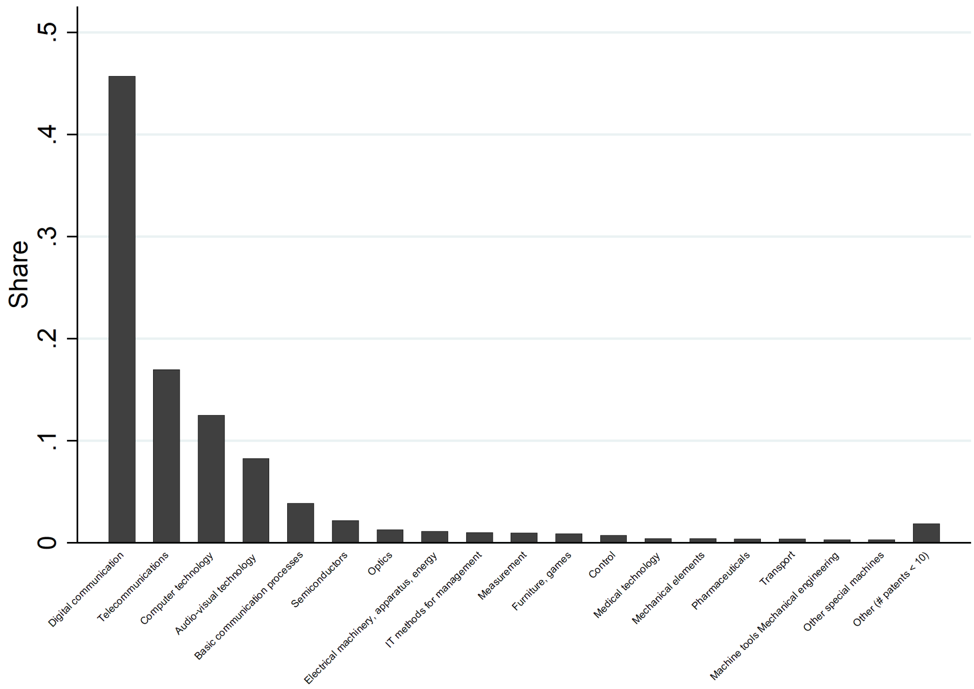
By considering only the high-tech patent applications, the share of PAE patent applications rises to 0.75% (3,082 patents at the EPO) of the entire basket of high-tech patent applications filed from 1997 to 2010 at the EPO. Considering only patents that have been granted, the share of PAE is 0.72% (1,095 patents at the EPO).

[28] http://www.wipo.int/ipstats/en/statistics/technology_concordance.html

[29] The definition of high-technology patents proposed by Eurostat uses specific sub-classes of the International Patent Classification (IPC) as defined in the trilateral statistical report of the EPO, JPO and USPTO. The following (macro) technical fields are defined as high technology: Computer and automated business equipment; Micro-organism and genetic engineering; Communications technology; Aviation; Semiconductors; Lasers. The list of sub-classes and their definition is provided by Eurostat at http://ec.europa.eu/eurostat/cache/metadata/Annexes/pat_esms_an2.pdf.

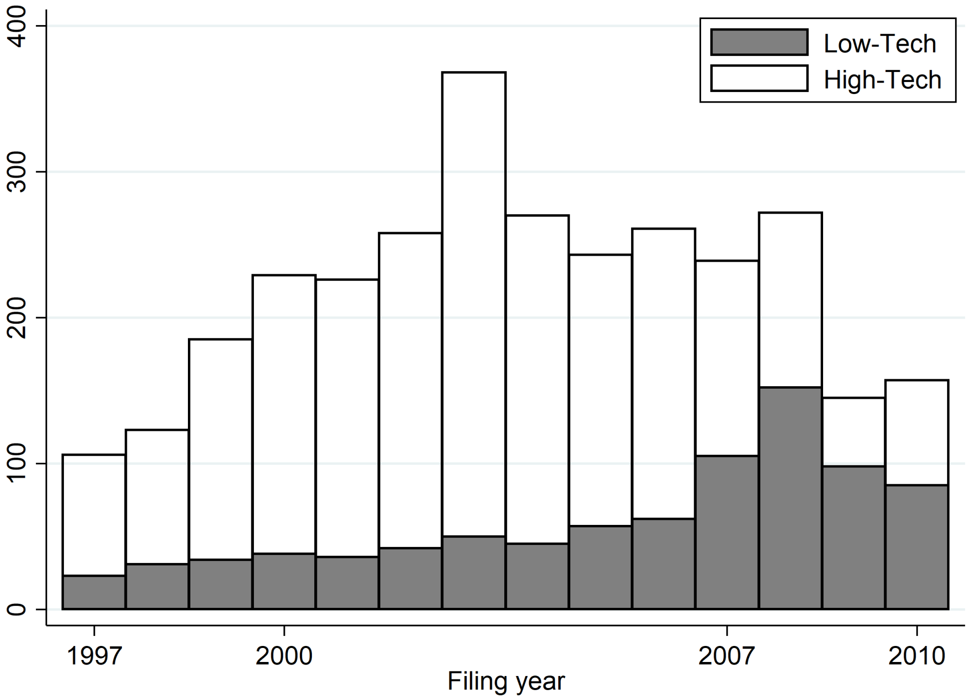
[30] For example, in the US, the number of lawsuits filed by PAEs against energy companies increased at a meaningful rate from 2006, when they accounted for about the 10% of all cases, to 2013, where they represented 30% (Morgan Lewis & Bockius LLP 2014. Are patent trolls now targeting the energy industry? – available at https://www.lexology.com/library/detail.aspx?g=c9476fdf-6e1c-4791-a3ce-46b1fef9dc82).

Figure 1: PAE patent applications by technological field (1997-2010)



Notes: The figure plots the distribution of PAE-owned patents at EPO per main technological area (Schmoch, 2008)

Figure 2: Number of PAE patent applications by filing year



Notes: The Eurostat definition of high-technology patents uses specic sub-classes of the International Patent Classification (IPC), as defined in the trilateral statistical report of the EPO, JPO and USPTO. See footnote 29.

The way of entering the European patent market The way of entering the European patent market may be through the patent filing or through a patent acquisition. Focusing on patent applications with at least one PAE as owner, we find that only less than 30% of them have been acquired after being first filed at the EPO (880 patent applications, 326 granted patents); the majority of them (2,202 – representing 71.45% of all PAE patent applications) are filed directly at the EPO by a PAE.[31] Of them, only 281 are transferred to PEs afterwards (12.76%). This share falls to 8.2% (63 patents transferred out of 769 patents filed by PAEs) if we consider only granted patents: this means that more than 90% of the granted patents acquired by PAEs are never transferred thereafter to PEs. Although PAEs might prefer to license than sell patents, the low share of patents sold raises questions about their role as intermediaries. Table 3 summarizes those numbers.

Table 3: The PAEs' way of entering the market: filing and acquisition

	Applications	**(%)**	**Granted**	**(%)**
Filed by PAEs	2,202	*71.45%*	769	*70.23%*
Transferred afterwards	*281 (12.76%)*		*63 (8.20%)*	
Acquired by PAEs	880	*28.55%*	326	*29.77%*
All PAE patents	3,082		1,095	
EPO	411,259		151,902	

Only High-tech patents are considered. Years of filing: 1997-2010.

Turning to the age of transferred patents, patents acquired by PAEs are on average older than patents acquired by PEs (Table 4). The age of the invention at the time of the patent transfer, proxied by the years that elapse between the filing date and the transfer date, is on average 2.3 years higher for PAEs than for PEs. Furthermore, on average, PAEs' patents receive a grant later than PEs' patents (8.9 vs. 6.8 years after the filing date).

Table 4: Average patent age at the first transfer and at the grant

	# of patents	**First transfer (years)**	**Grant (years)**
Acquired by PAEs	326	7.0	8.9
Acquired by PEs	32,983	4.7	6.8

Only granted transferred high-tech patents considered, originally applied by PEs. Years of filing: 1997-2010.

Patent technological quality Finally, we look at the patent technological quality to better describe the PAE activity at EPO. Precisely, we measure technological quality by means of three indicators derived from the patent literature. First, we take the number of forward citations, up to three years after the filing,[32] as a measure of the patent technological impact.[33] We then consider the originality index, as proposed by Trajtenberg et al. (1997) and refined by Hall et al. (2001). The index is based on backward citations and it measures the dispersion across technological classes of the cited patents: the higher the dispersion, the more original the patent. Finally, we consider the number of patent claims which determines the breadth of rights conferred to a patent and reflects its technological

[31] In most cases these are U.S. patents that are acquired by PAEs before being extended to the EPO.

[32] We consider a moving fixed-period time-window to control for the fact that older patents would receive on average more citations than more recent ones; moreover, we exclude long-term citations since they are more likely to derive from cumulative inventive activities linked to the strategy of the patent applicant.

[33] For a recent survey on the use of patent citations in social science research, see Jaffe and de Rassenfosse (2017).

quality and value (Lanjouw and Schankerman, 2004). As reported in Table 5, patents acquired by PAEs are on average of higher quality than both PE-acquired patents and patents that are never transferred, whatever the measure considered.

Table 5: Technological quality

	# of patents	# of forward citations (3 years)	Originality	# of claims
Never transferred	117,824	3.04	0.66	13.72
		(5.48)	(0.25)	(9.43)
Acquired by PAEs	326	4.52	0.70	16.29
		(7.28)	(0.22)	(11.64)
Acquired by PEs	32,983	3.25	0.67	14.03
		(5.79)	(0.25)	(9.61)

Only granted transferred high-tech patents considered, originally applied by PEs. Years of filing: 1997-2010. t tests on the equality of means reveal that, on average, patents acquired by PAEs are more cited, more original and with more claims than both never transferred patents and patents acquired by PEs. Standard deviation in parentheses.

4 Empirical strategy and variables

To investigate the effect of PAEs' entry into the European market for technology on innovation, we look at the pattern of citations received by the block of patents transferred to PAEs. Precisely, to the extent that citations measure the use of knowledge by follow-on researchers, if the transfers of patents to PAEs raise the opportunity-cost of R&D in technologies closed the ones protected by the patent – as the risk to be sued increases – then the citation rate to PAE-acquired patents should decline after the transfer.[34]

Our sample comprises 151,133 unique high-tech granted patents filed at EPO between 1997 and 2010. For each patent we collect information on its yearly number of citations received up to 2013,[35] building an unbalanced panel of 1,671,758 total observations.[36] We restrict our analysis to patents applied for by PEs, excluding applications filed directly by PAEs which, in the majority of the cases, are foreign applications that have been acquired by PAEs and then extended to the EPO. This is also coherent with our analysis that aims to evaluate the role of PAEs as intermediary entities.

4.1 Forward citations as an indicator of patent exploitation

We assess the impact of PAEs on innovation by looking at the pattern of citations the focal patent receives. We argue that the number of forward citations is an indicator of the fact that the patented technology is somehow used by innovating and producing companies (Trajtenberg, 1990), whether they are patent holders (or licensees) or other companies performing R&D activities, or both. Citations are reported in the patent document, provide a legal delimitation of the property right scope, and have been used in the literature to track knowledge flows (Jaffe et al., 1993; Jaffe and Trajtenberg, 1999; Maurseth and Verspagen, 2002; Bottazzi and Peri, 2003; Montobbio and Sterzi, 2011).[37] Since citations show the degree of novelty and the inventive steps of patent claims, they identify the

[34] Murray and Stern (2007) adopt a similar strategy. Precisely, the authors analyze the effect of the patent grant on the pattern of citations received by scientific papers.

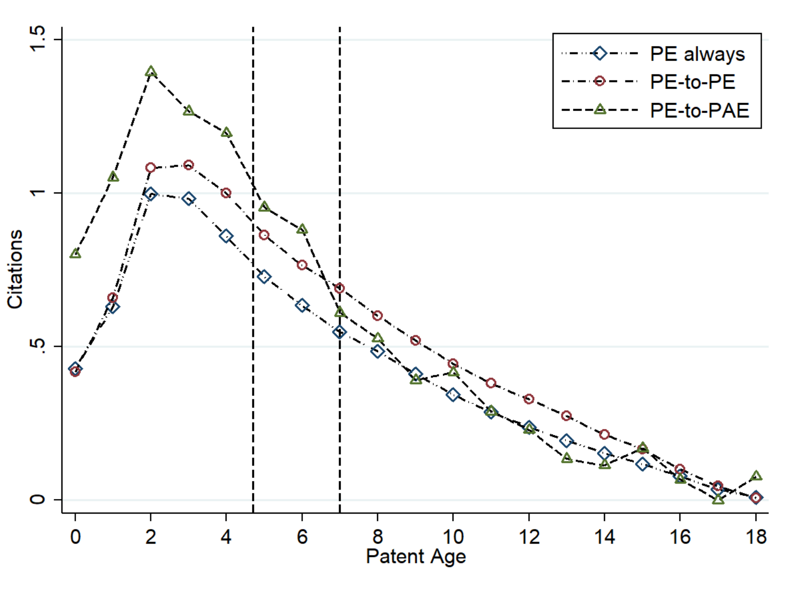
[35] Due to truncation issues, we collect citation data up to the year 2013. For this reason, we consider patents filed up to 2010.

[36] As described below, our sample reduces when we apply matching techniques.

[37] Griliches (1998) and Breschi et al. (2005) provide path-breaking and renowned surveys on the topic.

antecedents upon which the invention stands. In this respect, a citation from patent A to patent B indicates that part of the knowledge protected by patent B is also used in the technology protected by patent A. Controlling for the age and the domain, patents that stop being cited indicate that the protected technologies are likely to be no longer used in further inventions. Conversely, a high number of citations received indicates that the technological content of a patented invention is highly exploited by further inventors, reflecting its quality (Trajtenberg, 1990; Fischer and Leidinger, 2014). To account for the entire flow of citations a specific technology receives, we correct forward citations for DOCDB patent families.[38] Figure 3 shows the average yearly number of forward citations received by the group of patents applied by PEs and never transferred to any organization before the grant (*PE always*), the group of patents applied by PEs and transferred to other PEs (*PE-to-PE*) and, finally, the group of patents applied by PEs and later sold to PAEs (*PE-to-PAE*). From the figure, it emerges that the three types of patents share a similar citation age profile: the number of citations increases in the first two years from the filing date and then gradually decreases. However, it also emerges that patents subsequently sold to PAEs receive a larger number of citations in the first six years from the filing date and a lower number thereafter, suggesting that technologies protected by patents acquired by PAEs are, on average, less used after the transfer (which takes place, on average, after 7 years from the filing).

Figure 3: Age profile of citations



Notes: The figure draws the age profile of citations by category (never sold patents, patents transferred to PEs and patents transferred to PAEs). Vertical lines correspond to the average patent age at the time of the first transfer: 4.7 years for patents applied by PEs, 7 years for patents acquired by PAEs.

4.2 A triple differences approach (DDD)

To study the impact of PAEs on follow-on innovation activities we rely on a triple differences (DDD) research design in a panel data framework with patents that experience a change of ownership as the treated group and patents that are never transferred as the control group. We further split the treated group of patents into two groups: (1) patents transferred to PEs (*PE*); and (2) patents trans-

[38] For a complete discussion about the opportunity of correcting citations for patent families, see Martínez (2011).

ferred to PAEs (*PAE*). Our patent-level DDD setup accounts for common macroeconomic trends and observable technological characteristics. This specification allows us to examine the difference between the change in innovation diffusion by patents acquired by PAEs and the corresponding change by patents acquired by PEs.

Formally, we estimate the following empirical model to predict the yearly number of citations received by the patent i during its life.

$$\begin{aligned} Cit_{it} &= \alpha_0 + \alpha_1 PE_i + \alpha_2 PAE_i + \alpha_3 TRADED_{it} + \alpha_4 TRADED_{it} * PAE_i + \\ & +\alpha_5 Age_{it} + \mathbf{X_i'}\alpha_6 + \eta_i + \gamma_i + \varepsilon_{it} \end{aligned} \tag{1}$$

where Cit_{it} is the number of citations received by the patent i in the year t. PE_i is a dummy variable to indicate patents that are transferred to PEs, while PAE_i is a dummy variable for patents transferred to a PAE. The reference group is composed of patents applied by PEs and never traded (the group labeled "*PE always*" in Figure 3). $TRADED_{it}$ is an indicator of the post-traded event related to the first transfer: it is a dummy variable that identifies the change of ownership for each patent such that it is always zero for patents that are never transferred, while it takes the value one for transferred patents from the year of the transfer and in subsequent years. On one side, a positive sign of the dummy $TRADED_{it}$ might indicate that patent transactions enhance matching efficiency between technology suppliers and users. On the other side, a negative sign might indicate that patents are used and acquired mainly for strategic reasons (Hall and Ziedonis, 2001; Blind et al., 2009; Noel and Schankerman, 2013), which is often the case for complex technologies in general and for the high-tech sector in particular (Bessen, 2003; Orsenigo and Sterzi, 2010).

To control for the effect that the patent age may have on the number of forward citations, we include dummies (Age_{it}) for each year since the patent's priority filing (which is normalized to zero). $\mathbf{X_i'}$ is a vector of patent fixed characteristics that are potentially associated with patent forward citations. Their inclusion may improve the accuracy of the DDD estimate. Among these controls, we include the inventors' team size, patent originality,[39] dummies for the inventor's country of residence, number of patent claims, and dummies for patents applied by individuals and those applied by more than one applicant. Finally, η_i is a full set of filing year dummies used to control for all yearly shocks common to all industries and countries, such as business cycles, γ_i is a set of technological field dummies and ε_{it} is the error term. In some specifications, we estimate model 1 including directly patent fixed effects with the purpose of controlling for all time-invariant unobservable patent characteristics.

The description of the variables used in the empirical analysis and their sources are presented in Table 6. Summary statistics are presented in Table 7. DDD results are presented in Section 5.1.

Parameters α_1 and α_2 measure the difference in the average number of forward citations between the reference group of patents that have never been traded and the group of patents that are transferred to PEs (PE_i) and those that are transferred to PAEs (PAE_i), computed in the period before

[39] Patent originality is calculated according to Squicciarini et al. (2013). Quoting the authors, *"Patent originality refers to the breadth of the technology fields on which a patent relies. The patent originality measure, first proposed by Trajtenberg et al. (1997), operationalizes this concept of knowledge diversification and its importance for innovation: inventions relying on a large number of diverse knowledge sources are supposed to lead to original results (i.e. on patents belonging to a wide array of technology fields)"* [pag. 49]. Building on Hall et al. (2001), they define the originality indicator as: $Originality_p = 1 - \sum_j^{n_p} s_{pj}^2$. where s_{pj} is the percentage of citations made by patent p to patent class j out of the n_p IPC 4-digit patent codes contained in the patents cited by patent p. Citation measures are built on EPO patents and account for patent equivalents.

Table 6: Variables description and sources

Variable	Definition	Source
Citations	Number of yearly forward citations corrected for for DOCDB patent families	CRIOS-PATSTAT (Coffano and Tarasconi, 2014)
PE	Patent acquired by a PE (dummy)	European Patent Register
PAE	Patent acquired by a PAE (dummy)	European Patent Register
TRADED	Indicator of the post-traded event (=1 from the year in which the transfer takes place)	European Patent Register
FILING YEAR	Year of patent filing	OECD Patent Quality Indicators database (Squicciarini et al., 2013)
AGE	Number of years elapsed since the patent filing	European Patent Register
COAPPLICANT	Patent applied by two or more applicants (dummy)	European Patent Register
INDIVIDUAL	Patent applied by an individual (dummy)	European Patent Register
TEAM SIZE	Number of inventors	European Patent Register
ORIGINALITY	Patent originality index	OECD Patent Quality Indicators database (Squicciarini et al., 2013)
CLAIMS	Number of claims in a patent document	OECD Patent Quality Indicators database (Squicciarini et al., 2013)
PATENT STOCK	Applicant stock of patents at the time of the patent filing	European Patent Register
COUNTRY	Patent inventor's country of residence (dummy)	European Patent Register
TECHNOLOGY	OST7 technological domain (dummy)	CRIOS-PATSTAT (Coffano and Tarasconi, 2014)

Table 7: Summary Statistics

	Mean	St. Dev.	Min.	Max.
FORWARD CITATIONS (LN)	0.7	1.77	0	145
PE	0.2	0.42	0	1
PAE	0.002	0.048	0	1
TRADED	0.1	0.35	0	1
AGE	5.6	4.04	0	16
COAPPLICANT	0.05	0.21	0	1
INDIVIDUAL	0.02	0.13	0	1
TEAM SIZE	2.7	1.84	1	29
ORIGINALITY	0.7	0.25	0	1
CLAIMS	14.0	9.93	1	182
PATENT STOCK (thousands)	1.4	2.05	0.001	13.8
Observations	1,671,758			

Notes: Patent filing year between 1997 and 2010. For the variables description and sources, see Table 6.

the transfer. Positive signs for these parameters indicate that patents that will be transferred during their life are on average of higher quality than patents never transferred. In particular, a positive sign of α_2 indicates that PAEs "cherry pick" patents of high quality.

Our main interest focuses on parameters α_3 and α_4. The parameter α_3 identifies the effect of a market transaction on the number of citations received by patent i at time t, when the buyer is a PE. Two main forces drive the sign of this coefficient. On one side, the (secondary) patent market is likely to facilitate the match between buyers and sellers, so that the patent transaction promotes innovation (positive effect). On the other side, if the patent is acquired for strategic reasons, its transfer will be detrimental to its further usage (negative effect). The parameter α_4 is the difference-in-difference-in-differences estimator and identifies the impact of PAEs on patent forward citations. A positive sign of α_4 indicates that transferring a patent to a PAE, rather than to a PE, increases the chance that the technology protected by the patent will be subsequently used and exploited by innovating firms (*market-makers* hypothesis). On the contrary, a negative sign indicates that patents acquired by PAEs start receiving fewer citations after the transfer as compared to patents sold to PEs, suggesting that PAEs do not facilitate cumulative innovation, but rather stand in its way (*market-breakers* hypothesis). Finally, the combination of α_3 and α_4 identifies the effect of market transactions on the citations path when the patent is acquired by a PAE (with respect to never-transferred patents).

4.3 Propensity score matching and conditional DDD

One might question that the fact that the decision to transfer a patent is not exogenous. Exploiting the longitudinal dimension of our data guarantees that relevant issues related to unobservable factors are taken into account. However, a bias due to observable variables is likely to still remain. For example, patent characteristics such as the age of the patent, the number of citations received by a given age, and the patent generality may influence the probability that a patent is transferred (Serrano, 2010).

In particular, we may expect companies to target patents in high-growth technological sub-domains, resulting in an increasing trend in the citations path after the transfer occurs and implying a positive bias in the coefficient for the dummy $TRADED_{it}$.

In presence of potential biases due to selection into treatment, the DDD model may produce non-consistent estimates, even when it controls for observed variables that might influence both the outcome and the treatment. To partially overcome biases due to observable factors, we apply matching methods. Matching methods seek to replicate a randomized experiment in which the matched and the control patents do not differ systematically from each other on observable variables. Consequently, we match patents that are transferred (either to PAEs or to PEs) and non-transferred patents on an index, the propensity score, of several characteristics affecting the likelihood of a transfer occurring.

Precisely, these characteristics include: the age of the patent; the average number of citations received in the 4-year time window elapsing from the filing[40], the level of patent originality and the number of patent claims, as proxies for the patent technological quality; the number of backward citations; the technological sub-field in which the invention belongs to (accounting for intrinsic technological fixed characteristics); the size of the inventors' team; the nature of the applicant (individual vs. company); the size of the first applicant (proxied by the applicant's stock of patents); and the inventor's country of residence. Since we look at the first four years after the filing to both count the number of forward citations and measure the patent technological quality, we drop patents that have been transferred within this time window from the analysis.

The propensity score is then calculated from the fitted values of a probit model where the dependent variable is the probability of a patent transfer.

We adopt the nearest-neighbor algorithm, using the information from up to five neighbors and setting a "caliper" threshold to 0.1.[41] As Caliendo and Kopeinig (2008) illustrate, the choice of the algorithm to use is a matter of a trade-off between bias and efficiency. Using up to 5 control units to proxy for the counterfactual situation allows us to gain efficiency in the estimation, while the caliper threshold, which imposes a tolerance level on the maximum propensity score distance, reduces potential bias, avoiding bad matches.

Through matching techniques we are able to ensure that the treated and the control groups should be on average observationally identical. Nevertheless, selection on unobservables still represents a relevant concern and might bias the estimation. For this reason, we maintain the structure of the data as described in Section 4.2 and we follow a conditional difference-in-difference-in-differences (CDDD) strategy.

While the analyses described so far lead us to interpret the role of PAEs from a very comprehensive perspective, we acknowledge that they come at the cost of not entirely solving endogeneity issues. The patent transfer is indeed an endogenous event since we cannot properly control for entities' strategies. Even if we are close to replicating a hypothetical experiment by both performing matching techniques and exploiting the longitudinal nature of our data, an intrinsic source of bias is likely to remain.

When it comes to exploring the direction of the bias, we propose the following kind of interpretation. Due to both strategic patenting and merger and acquisition (M&A) events that we are not able to directly capture, the direction of the bias should reduce the (positive) magnitude of the TRADED effect. Strategic patenting activities are indeed essentially devoted to block potential competitors. Patents acquired strategically have a low likelihood of being further applied in R&D

[40] The choice of considering four years for citations is due, on the one hand, to the fact that patents receive the majority of citations in the first four years from the filing and, on the other hand, to the fact that the first transfer occurs, on average, after four years when PEs are buyers. For robustness we also count citations only up to the second year after the filing: results are consistent with those presented in Table 10 and available upon request by the authors.

[41] Estimations with the caliper treshold set at 0.01 provide similar results.

activities. Similarly, M&As are complex deals in which patent assets are likely to constitute a minor part. Therefore, once acquired, they will not necessarily be used by the buyer. As a consequence, we are likely to underestimate the clean effect of a 'pure' patent transaction on the follow-on utilization of the transferred patent.

Looking next at different strategies followed by PEs and PAEs in patent purchases, while PEs target patents that are strategic for their R&D activities, we argue that PAEs are instead more likely to specifically target patents characterized by high levels of applicability within the technological domain where they operate. Such patents are indeed more useful to sue producing companies for infringement. The likelihood of receiving citations for PAEs' patents – as an indicator of technological patent quality – may thus, in this case, be systematically higher than for PEs' patents. Importantly, PEs are involved several times in transactions in which patents are just complementary assets, not necessarily the core of the deal (i.e. M&As). Conversely, PAEs' structure and strategy are essentially built to either acquire patents to monetize them or inherit patents from unsuccessful operating companies (Shapiro and Scott-Morton, 2014; Scott Morton and Shapiro, 2016). Since patents are almost the only asset PAEs have, it is reasonable to assume that they are on average more accurate than PEs in building up their patent portfolios. As a result, such different strategies are likely to make the average qualitative level of patents acquired by PAEs systematically higher than the level of those acquired by PEs.

Anticipating the main results that we will describe in the next Section, we find that patents acquired by PAEs experience a drop in the number of citations received after the transfer. Thus, if patents targeted by PAEs are intrinsically more likely to receive citations, the real effect should probably be even more negative than the one we measure through both the DDD and the CDDD approaches.

5 Results

In this section we present the results from the two main empirical approaches proposed in Section 4. We begin in Section 5.1 with a baseline evaluation of the impact of the patent acquisition by a PAE on the number of patent forward citations using the patent-level DDD research design. In Section 5.2 we test the robustness of the baseline results by refining our measures based on patent citations. We then question the exogeneity of the patent transfer and present the results from the CDDD approach in Section 5.3.

5.1 Baseline Results

With respect to Equation 1, we take the logarithm transformation of the dependent variable and we estimate OLS models.[42] We also cluster standard errors at the patent level to control for possible serial correlations (Bertrand et al., 2004). Table 8 presents the estimation results. Different specifications refer to the inclusion in the specification of different controls. To interpret the magnitude of the coefficients, we refer to model (4) which contains the full set of control variables.

The dummy *PE* coefficient is significant and positive. Holding everything else constant, PEs acquire patents that are above the average in terms of citations received (precisely, before the time

[42] In the logarithm transformation we add one to all values. As patent counts take only non-negative integer values, we further estimate count models which give similar results and are presented in Table A-7 (Appendix A-3).

of the transfer, those patents receive 1.7% more citations per year than patents never transferred). Interestingly, patents transferred to PAEs (dummy PAE) receive on average 5.4% more citations, before the transfer, than patents never sold in the patent market, meaning that patents acquired by PAEs are on average of higher quality than those never transferred.[43] This result, in line with Fischer and Henkel (2012), is in conflict with the common feeling that PAEs' patent portfolios are mainly constituted of sparse and low-quality technologies.

The dummy $TRADED$ is an indicator of the post-traded event and, when it is not interacted with the dummy PAE, it refers to patents sold to practicing entities. The associated parameter (α_3 in the Equation 1) is 0.003 and is statistically non significant, meaning that PE-acquired patents do not experience significant changes in their citations pattern during the post-transfer period.

The interaction term $TRADED * PAE$ identifies the additional effect of the transfer when the trade involves a PAE. The coefficient is -0.057, meaning that patents transferred to PAEs receive around 5.7% fewer citations than patents transferred to PEs. The net effect of the transfer to a PAE on the patent citation rate is thus negative, implying a reduction of 5.7% in the number of citations in the years subsequent to the transfer.

Model (5) controls for all unobservable time-invariant characteristics at the patent level which may have an impact on the yearly number of citations. The negative impact of PAEs on forward citations further increases in absolute value: the patent transfer to a PAE is associated with a reduction of 7.5% in the number of citations after the transfer compared to a patent transferred to a practicing entity. The net effect of the transfer to a PAE is -6.64%. It is worth noticing indeed that the dummy $TRADED$ is now significant and positive (+0.86%), suggesting that markets for technology may facilitate the transfer of technologies to actors that are in a better position to profit from them (Arora et al., 2004). However, as previously discussed, the effect of the patent transfer might be over-estimated in presence of potential biases due to selection into treatment (i.e. companies may tend to acquire patents in high-growth technological domains, where citations flow rapidly and with higher rates.)

5.2 "Strategic" citations and the "in house" effect

On one hand, results presented in Section 5.1 indicate that PAEs acquire patents that are on average of high quality. On the other hand, they tend to confirm the *Market-breakers* hypothesis stated in Section 2.2.

To assess the robustness of these results, we first exclude the number of citations added by the applicant from the total number of forward citations. Indeed, one might think that actors involved in R&D projects in fields related to those in which PAEs are active may strategically decide not to cite patents owned by PAEs, if they perceive an augmented risk of being sued. If this is the case, we would over-estimate the overall negative effect of PAEs' patent acquisitions on follow-on innovation activities: the patent purchase by a PAE would impact only the citation paths without reducing innovation. In order to discard this possibility, we consider only citations added by the patent examiner. Results proposed in Table 9 confirm the general ones, revealing that this source of bias is only marginally present. The coefficient of the interaction term $TRADED * PAE$ is still significant and negative, although it reduces from -5.7% (Table 8, Column 4) to -4.9% (Table 9, Column 4). The dummy $TRADED$ remains non significant.

[43]Coefficients about the dummies PE and PAE are statistically not different, meaning that the average quality of the

Table 8: Baseline models

	(1)	(2)	(3)	(4)	(5)
	Raw	**Raw**	**Raw**	**Raw**	**Raw**
PE	0.039***	0.038***	0.018***	0.017***	
	(0.0032)	(0.0032)	(0.0031)	(0.0030)	
PAE	0.073***	0.098***	0.062**	0.054*	
	(0.024)	(0.029)	(0.028)	(0.028)	
TRADED	-0.023***	-0.023***	0.0027	0.0030	0.0086***
	(0.0031)	(0.0031)	(0.0031)	(0.0030)	(0.0022)
TRADED*PAE		-0.063**	-0.060**	-0.057**	-0.075***
		(0.027)	(0.027)	(0.026)	(0.023)
TEAM SIZE (LN)				0.069***	
				(0.0023)	
ORIGINALITY				0.084***	
				(0.0035)	
CLAIMS (LN)				0.095***	
				(0.0017)	
COAPPLICANT				-0.0062	
				(0.0047)	
INDIVIDUAL				-0.013*	
				(0.0075)	
PATENT STOCK (LN)				-0.00026	
				(0.0013)	
Age FE	Yes	Yes	Yes	Yes	Yes
Filing Year FE	No	No	Yes	Yes	No
Technology FE	No	No	Yes	Yes	No
Country	No	No	Yes	Yes	No
Patent FE	No	No	No	No	Yes
Observations	1,671,758	1,671,758	1,671,758	1,671,758	1,671,758
# of Patents	151,133	151,133	151,133	151,133	151,133
Adjusted R^2	0.033	0.033	0.065	0.081	0.403
F	51.8	39.8	92.4	193.8	11.9

All the models use the raw number of forward citations as the dependent variable (log transformed). Column (1) reports our most parsimonious specification, without our interaction of interest and with only patent age dummies as covariates. In column (2) we add our interaction of interest. In column (4) we also control for a series of dummies: patent filing year, inventor's country of residence and technological domain. Column (4) includes the full set of covariates and is our preferred specification. Model in column (5) includes patent fixed effects. Clustered Standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$

Table 9: Baseline models (Exclusion of Citations added by the applicant)

	(1)	(2)	(3)	(4)	(5)
	No Appl	**No Appl**	**No Appl**	**No Appl**	**No Appl**
PE	0.030***	0.029***	0.015***	0.015***	
	(0.0026)	(0.0026)	(0.0026)	(0.0025)	
PAE	0.071***	0.092***	0.053**	0.046*	
	(0.020)	(0.025)	(0.024)	(0.024)	
TRADED	-0.025***	-0.024***	-0.0039	-0.0036	-0.00083
	(0.0026)	(0.0026)	(0.0025)	(0.0025)	(0.0020)
TRADED*PAE		-0.053**	-0.052**	-0.049**	-0.064***
		(0.023)	(0.023)	(0.023)	(0.021)
TEAM SIZE (LN)				0.053***	
				(0.0019)	
ORIGINALITY				0.066***	
				(0.0028)	
CLAIMS (LN)				0.076***	
				(0.0013)	
COAPPLICANT				-0.0061*	
				(0.0035)	
INDIVIDUAL				-0.0078	
				(0.0059)	
PATENT STOCK (LN)				0.0040***	
				(0.0011)	
Age FE	Yes	Yes	Yes	Yes	Yes
Filing Year FE	No	No	Yes	Yes	No
Technology FE	No	No	Yes	Yes	No
Country	No	No	Yes	Yes	No
Patent FE	No	No	No	No	Yes
Observations	1,671,758	1,671,758	1,671,758	1,671,758	1,671,758
# of Patents	151,133	151,133	151,133	151,133	151,133
Adjusted R^2	0.041	0.041	0.069	0.082	0.352
F	46.0	35.2	112.3	207.4	4.82

All the models use the number of applicant-excluded forward citations as the dependent variable (log transformed). Column (1) reports our most parsimonious estimation without our interaction of interest, with only patent age fixed effects included. In column (2) we add our interaction of interest. In column (4) we also control for a series of dummies: patent filing year, inventor's country of residence and technological domain. Column (4) includes the full set of covariates and is our preferred specification. Model in column (5) includes patent fixed effects. Clustered Standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$

Finally, as a further robustness test, we also exclude self citations at the applicant level from the count of forward citations that the focal patent receives.[44] Results are reported in Appendix A-3 (Table A-5) and largely confirm the extant evidence. It is interesting to observe that now the estimated coefficient for the dummy $TRADED$ is negative and significant. It is useful to remember here that the coefficient for $TRADED$ captures the effect of the patent transfer on the number of follow-on citations received, when the buyer is a PE. By excluding self citations, we thus largely discard the effect of the transfer on the "in house" innovation activity performed by the patent buyer (and by PEs within the control group).

Importantly for our analysis, when we exclude self-citations from the count, we are likely to insert a (mechanical) source of bias affecting the interpretation of the interaction $TRADED * PAE$. PAEs are indeed, by definition, essentially non practicing. Conversely, net of strategic operations, PEs acquire patents to build on further inventions. The exclusion of self-citations from the count will thus mechanically reduce the role of PEs' patent acquisitions. Coherently, the real effect of the interaction $TRADED * PAE$ is likely to be even more negative than the one estimated in Table A-5, Column 4 (-5.5%).

In all, PAEs target patents revealing high-quality technological content. However, once acquired, those patents experience a strong decline in their citation path. This evidence tends to strengthen the *Market-breakers* hypothesis stated in Section 2.2.

5.3 PSM and CDDD

As highlighted in Section 4.3, one might question that the fact that a patent is traded is not exogenous. To partially overcome this source of bias further, we apply matching methods, seeking to replicate a randomized experiment in which the matched and the control patents do not differ systematically from each other on observable variables (as described in Section 4.3). More precisely, we match patents that are transferred (either to PAEs or to PEs) and non-transferred patents on an index, the propensity score, of several characteristics affecting the likelihood of a transfer occurring (Serrano, 2010). The list of variables selected to perform the matching concerns a comprehensive set of patent, applicant and inventor characteristics (see Section 4.3). The tests performed on the quality of the matching reveals that the adopted procedure successfully corrects for the selection on observable factors (Appendix A-2 is dedicated to an in-depth analysis of the tests performed for assessing the quality of the matching).

Once the propensity scores are calculated and the quality of the matching procedure adopted assessed, we present the results of the CDDD estimation in Table 10. As described in Section 4.3, we replicate the strategy proposed in Section 4.2 over the reduced sample resulting from the PSM. We thus again estimate Equation 1, including the full set of control variables or, alternatively, controlling for time invariant patent characteristics. Our dependent variables (and all the variables related to patent citations that we use for implementing the relative matching) are the raw count of citations (Columns 1 and 2), the count of citations with the exclusion of those added by the patent applicant (Columns 3 and 4), and the count of citations with the exclusion of self citations (Columns 5 and 6).

Results, reported in Table 10, confirm the main findings highlighted in Section 5.1 and in Sec-

transferred patents is not significantly different between PEs and PAEs.

[44]This new dependent variable shows a correlation of 0.842 with the variable constructed excluding the number of citations added by the applicant from the total number of forward citations.

tion 5.2.[45] The main partial difference from the baseline results is the role played by the dummy *TRADED*. Once patents that are transferred (either to PAEs or to PEs) have been matched to non-transferred patents on observable characteristics, we do indeed find that, after the transfer, the former receive fewer citations. This result may be explained by the increasing incidence of strategic patent acquisitions in the ICT domain (Hall and Ziedonis, 2001; Blind et al., 2009; Noel and Schankerman, 2013). Strong technological complementarities and standardization, typical of the high-tech sector, lead to a mutual hold-up among innovators and to the fragmentation of the relevant IP ownership (Orsenigo and Sterzi, 2010). In this context, the exploitation of cross-licensing agreements and the ability both to avoid the hold-up problems and attract venture capital funding are often the main reasons for patent acquisitions (Hall and Ziedonis, 2001).

Importantly, the effect of a patent transfer to a PAE on the follow-on use of the protected technology is negative and significant in all the specifications. More precisely, according to the estimates reported in Column 1 (where the dependent variable is the raw count of citations), the transfer of a patent to a PAE reduces the yearly number of forward citations it will receive by 6.4% compared to patents transferred to practicing entities. Comparing this result with the ones from the baseline estimations (Table 8, Column 4), we find that the net effect is even more negative, going from -5.7% to -7.8%.[46]

6 Conclusions

The proliferation of PAEs has become a topic of intense academic debate and an important public policy issue. On the one hand, critics suggest that the PAE enforcement model imposes costs that are disproportionate to the value of the patented technology, while their litigation targets – often operating companies – have fewer defensive options since PAEs neither produce goods nor perform R&D: as a result, PAEs are responsible for a deadweight loss to the economy by discouraging operating companies from innovating. On the other hand, advocates of the PAE business stress that their patents are often stronger than those held by operating companies and that they serve as intermediaries in the market for invention, injecting liquidity, enhancing the enforcement of IPRs and making the matching between technology users and producers more efficient.

The goal of this paper is to enrich the debate by providing new evidence based on the patenting activity of PAEs in Europe, a region where the patent assertion landscape is growing rapidly and the imminent introduction of the Unified Patent Court (UPC) and the Unitary Patent (UP) are likely to be "game-changing events that could increase the amount of patent assertion activity in Europe" (Thumm, 2018).

By exploiting a unique database of patent transfers involving PAEs at the European Patent Office, we find that the presence of PAEs in Europe is not marginal. When considering only high-tech patent applications, the share of those involving at least one PAE as either first applicant or buyer constitutes 0.75% of the entire basket of high-tech patent applications filed from 1997 to 2010 at the EPO.

Furthermore, we investigate the impact of PAEs' business model on innovation by looking at the pattern of citations received by patents acquired by PAEs. Building on the idea that citations are an

[45]For robustness, we also exclude one by one control variables from our estimates. Results do not change significantly.

[46]The same evidence appears when comparing the estimates from Column 3 with estimates from Column 4 in Table 9, and when comparing the estimates from Column 5 with estimates from Column 4 in Table A-5.

Table 10: Conditional DDD estimation

	(1) **Raw**	(2) **Raw**	(3) **No Appl**	(4) **No Appl**	(5) **No Self**	(6) **No Self**
PE	0.024***		0.018***		0.049***	
	(0.0033)		(0.0027)		(0.0031)	
PAE	0.069**		0.056**		0.099***	
	(0.028)		(0.024)		(0.027)	
TRADED	-0.014***	-0.013***	-0.014***	-0.013***	-0.027***	-0.028***
	(0.0032)	(0.0023)	(0.0026)	(0.0020)	(0.0031)	(0.0022)
TRADED*PAE	-0.064**	-0.079***	-0.055**	-0.068***	-0.066***	-0.084***
	(0.025)	(0.022)	(0.022)	(0.021)	(0.025)	(0.022)
TEAM SIZE (LN)	0.062***		0.048***		0.053***	
	(0.0029)		(0.0022)		(0.0027)	
ORIGINALITY	0.084***		0.063***		0.077***	
	(0.0041)		(0.0032)		(0.0039)	
CLAIMS (LN)	0.083***		0.065***		0.075***	
	(0.0020)		(0.0016)		(0.0019)	
COAPPLICANT	-0.0046		-0.0058		0.019***	
	(0.0051)		(0.0036)		(0.0049)	
INDIVIDUAL	-0.0059		-0.00027		0.0057	
	(0.0091)		(0.0070)		(0.0088)	
PATENT STOCK (LN)	-0.0057***		-0.00046		-0.0042***	
	(0.0016)		(0.0013)		(0.0015)	
Age FE	Yes	Yes	Yes	Yes	Yes	Yes
Filing Year FE	Yes	No	Yes	No	Yes	No
Technology FE	Yes	No	Yes	No	Yes	No
Country	Yes	No	Yes	No	Yes	No
Patent FE	No	Yes	No	Yes	No	Yes
Observations	1,551,996	1,551,996	1,551,996	1,551,996	1,551,996	1,551,996
# of Patents	115,440	115,440	115,440	115,440	115,440	115,440
Adjusted R^2	0.110	0.389	0.109	0.337	0.104	0.366
F	109.8	23.9	115.3	29.4	109.8	94.1

Models (1) and (2) use the raw number of forward citations as the dependent variable (log transformed). Models (3) and (4) use the number of applicant-excluded forward citations as the dependent variable (log transformed). Finally, Models (5) and (6) use the number of self-citation-excluded forward citations as the dependent variable (log transformed). Models (1), (3) and (5) include the full set of controls. Models (2), (4) and (6) include patent fixed effects. Clustered Standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$

indicator of the use of the protected technology by innovating and producing companies, we assume that a patent that stops being cited indicates that the protected technology is likely to no longer be used in further inventions. We thus compare citations received by patents acquired by PAEs, before and after the transfer, with citations received by patents that are either never transferred or that have been acquired by other PEs.

Is the typical PAE business model harmful for innovation processes? According to our results we can conclude that, on average, the entry of PAEs in the patent market implies a significant reduction in the citation rate of the patents they buy. This evidence suggests that innovators active in technological areas where PAEs operate may have been forced to pay PAEs (either because they lost a lawsuit or settled out of court) or, more generally, may perceive an augmented risk of being sued, with the consequence of reducing their R&D effort in such fields. The role of PAEs as intermediaries seems not to be very significant. However, our results also show that patents acquired by PAEs are, on average, of higher technological quality than those never transferred. In principle, PAEs may thus perform the socially valuable function of creating a "capital market for invention" by providing incentives for individual and small inventors and making the patent market more liquid (McDonough, 2006; Myhrvold, 2010). To sum up, the question whether PAEs negatively impact on innovation processes is thus still open, although the fact that PAEs transfer only a small fraction of their revenues to original patent inventors (Bessen et al., 2011) speaks in favor of an affirmative response.

Our analysis is not without its limitations. First, it would be worth bringing our study of PAEs and patent intermediation closer to reality by adding information on licensing agreements to our setting. Indeed, we do not observe any transactions which do not involve patent transfers and we thus unavoidably underestimate the presence of PAE business in the patent market. However, there are many cases in which companies, instead of selling their patents to patent intermediaries, opt for licensing their technologies.

Second, we observe only patent transfers that occur during the granting process, again underestimating the presence of PAEs in the patent market. Observing data on patent transfers occurring after the grant would permit a better study of the strategies pursued by PAEs to enter the market. PAEs are in fact often accused of buying and litigating patents as late as possible, when the unsuspecting infringers have already started the production of goods based on technologies protected by the patents concerned, so as to maximize licensing fees.

One last remark concerns the policy implications of our work. In order to keep PAEs from reducing innovation and to protect legitimate patent holders, some economists and legal scholars have recommended reforming national patent offices by requiring them to conduct an open review whenever a patent is sold or renewed (Barker, 2005) and, in general, to improve the quality of patents issued (Bradford and Durkin, 2012). While the former recommendation would be likely to increase the transparency of patent transactions, thereby reducing the incentives of opportunistic behavior, the latter would instead probably be neutral with respect to PAEs' strategies. Indeed, while it is true that these policy reforms would reduce the number of weak patents issued – guaranteeing a more efficient market for intellectual property rights – it is also true that patents acquired by PAEs are on average not so weak. In all, by intervening on the market entry-side, there is the risk of reducing the incentives for all kind of intermediaries, with no clear consequences on the net efficiency of the whole IPR system.

The negative consequences of PAE business on innovation mainly derive from the use that PAEs make of their high-quality acquired patents. Many of these patents stop being used, meaning that producing and innovating companies either interrupt their R&D investments or shift technological domains in order to avoid future litigation. From this point of view, any kind of legislative attempt aiming at reducing the cost of litigation and at increasing the alignment between the innovation reward and contribution might help reduce the incentive to behave opportunistically, partially avoiding the negative consequences of PAEs on innovation (Merges, 2009; Scott Morton and Shapiro, 2016).

As a general conclusion, policy interventions should point to the necessity of the presence of real intermediaries in the technology market – due to its intrinsic characteristics of illiquidity and matching difficulties – to ensure second best solutions, minimizing the presence of entities whose purpose is only to take advantage of imperfections residing in the middle of the possible deal between technology users and producers.

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Appendix

A-1 Harmonization and disambiguation of applicant names at the EP Register

European Patent Register (EPR) assigns to each recorded applicant a unique internal identifier based on a combination of the fields "NAME" and "ADDRESS". As stressed above, several incongruences could emerge in identifying patent-ownership changes, essentially because applicants' identities have not been harmonized or disambiguated before being listed in the EPR database (De Rassenfosse et al., 2017). Indeed, if the same applicant changes name and/or address in its patenting life, the database will automatically assign a new event for all the patents it owns, with a new identifier attached (without updating the former one). Similarly, if the same applicant owns two patents, but the name and/or the address have been recorded differently in the two original documents (i.e. due to typing errors or different abbreviations), two different identifiers will be assigned accordingly. These incongruences thus represent a relevant source of bias when analyzing changes in patent ownership and when matching this source of data with external information.

To overcome this issue and partially reduce the number of false positives when analyzing patent legal events, we harmonize and standardize applicants' names and addresses. Since original EP-Register data on applicants' names and addresses come in a text string, we pre-process the data as follows:

1. *Parsing, cleaning and standardizing applicants' names.* The original text string for applicants' names is parsed into relevant sub-components, cleaned by removing special characters and stop words, and standardized with respect to abbreviations for business entities. In this step, we apply the STATA utility *"stnd_compname"* (Wasi and Flaaen, 2015).[47]

2. *Parsing, cleaning and standardizing applicants' addresses.* Similarly, the original text string for applicants' addresses is parsed into relevant sub-components, cleaned by removing special characters and stop words, and standardized for abbreviations. In this step, we apply the STATA utility *"stnd_address"* (Wasi and Flaaen, 2015). Moreover, we isolate and standardize the country field from the applicant's address.

Based on cleaned names and addresses, we re-assign to each original applicant four new internal identifiers, following different rules: i) a new identifier (*id_name_and_address*) grouping applicants showing the same name and complete address; ii) a new identifier grouping applicants sharing the same name and the same country (*id_name_and_country*); iii) a new identifier grouping applicants showing the same name, independently from the address (*id_name*); iv) a new identifier grouping applicants showing the same complete address, independently from the name (*id_address*). The first identifier follows the same logic adopted by EPR, but it groups original applicants more precisely than EPR does (reducing the number of false positives and still minimizing the number of false negatives). Conversely, the other identifiers go for higher recall, but at the cost of being less precise (they reduce the number of false negatives, but at the cost of allowing for higher numbers of false positives).

[47]We extend the standardization procedure proposed by Wasi and Flaaen (2015) by extending the list of abbreviations for company names to countries different from the US. Precisely, we add abbreviations usually appearing in Germany, the UK, France, Italy, Spain, Denmark, Sweden, Switzerland, Finland, Russia, and Japan.

A-1.1 Further refinement: String similarity within parties involved in possible patent transfers

As a second step performed to augment the precision in capturing patent transfers, we directly focus on patents showing potential transaction events during the granting phase. Within applicant names listed in the same patent document, we apply the STATA tool MATCHIT (Raffo, 2015) to assign a probability that two unique parties are actually the same. More precisely, MATCHIT is a tool developed to join observations from two data-sets based on string variables which do not necessarily need to be exactly the same. It allows for a fuzzy similarity between two different text variables. We consider two unique entities as the same according to three different similarity thresholds (0.9, 0.95 and 0.99). Coherently, we assign three new internal IDs by applying transitivity to the entire universe of applicants listed in the EPR database.

According to steps 1 and 2, we end up with a final sample of 470,169 unique applicants (adopting the *id_name_and_country* identifier and fixing the similarity threshold at 0.95). This means a reduction in the raw number of unique customer IDs of 35.15%. Looking at the transfers individuated, they are responsible for 606,347 patents with at least one change in the applicant field recorded (20.92% of the total number of applications registered at EPO). For 221,719 applications, the potential transfer emerging from the raw data seems just to be a change in the applicant's name or address. Table A-1 reports the number of patent transfers according to the three thresholds applied, taking fixed the *id_name_and_country* built in step 1.

Table A-1: Applicant names consolidation in EP Register: Number of transfers

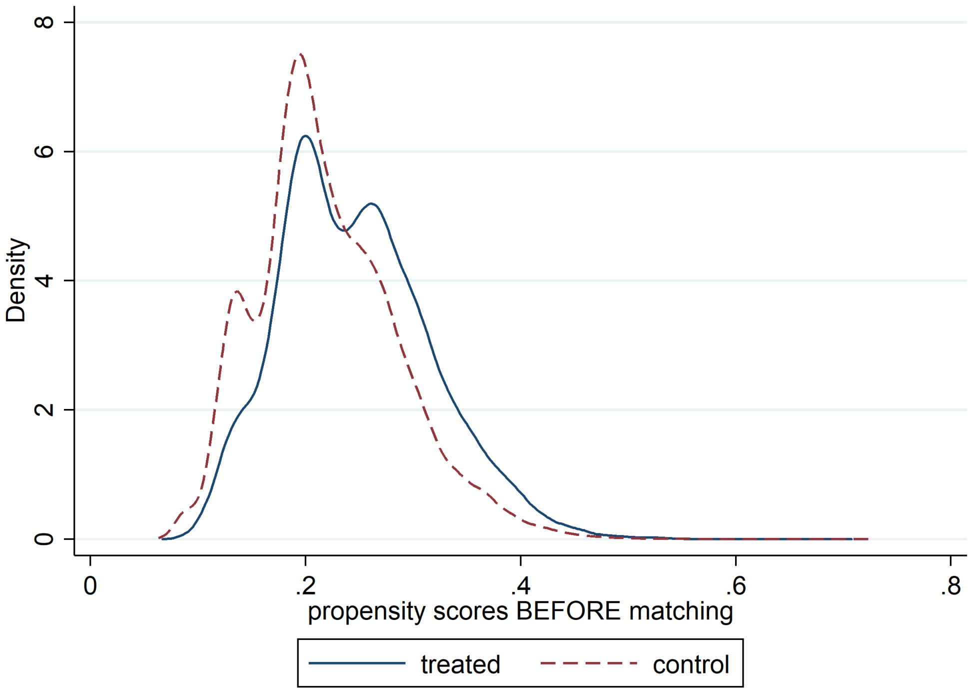
MATCHIT threshold	EPR raw	EPR cleaned	Difference
0.9	828,066	596,845	-28.04%
0.95	828,066	606,347	-26.78%
0.99	828,066	608,444	-26.52%

Notes: The Table reports the reduction in the number of potential patent transfers individuated at EPO once consolidated the applicant identities.

A-2 Matching quality

This Section will describe the quality of the matching methods we implemented to perform the conditional DDD estimates. First, we check whether the common support condition holds. This condition ensures that we estimate only effects in regions where two observations, one belonging to the treated and the other to the control group, can have a similar participation probability. Figure A-1 displays a graphic analysis of the kernel density distribution for the two groups, before the implementation of the matching.[48] Though the shape of the two distributions differs, there is a large overlap between the distribution of the propensity score of the treated and the control group, ensuring that the common support condition holds.

Figure A-1: Kernel density distributions of the propensity score before the matching



Second, we check whether the matching on the propensity score actually manages to balance the distribution of the relevant variables in the control and the treatment groups. The literature suggests several methods to evaluate the matching quality. A common methodology, first introduced by Rosenbaum and Rubin (1985), is the two-sample t-test to check for significant differences in covariate means, for both groups, before and after the matching. Table A-2 reports the t-test for all the covariates we included in the probit regression to estimate the propensity score for the unmatched and the matched samples.

As expected, before the matching, there is a significant difference in the mean between the treated and the control group for several variables. However, all these differences are no longer statistically significant after implementing the matching procedure, confirming its good performance in balancing the covariates.

Furthermore, to asses the size of the bias reduction obtained through the propensity score match-

[48] Lechner (2001) argues that it is possible to assess the overlap between sub-samples through a graphic analysis of the propensity score density distribution for the treated and the control group, before the matching.

Table A-2: Descriptive statistics for the Unmatched and the Matched Sample

Variable	Unmatched (U) Matched (M)	Mean		%reduct		t-test	
		Treated	*Control*	*%bias*	*|bias|*	*t*	*p>t*
4Y FORWARD CITATIONS (LN)	U	0.04149	0.04074	0.5		0.82	0.413
	M	0.04149	0.04141	0.1	88.5	0.07	0.941
CLAIMS (LN)	U	2.538	2.519	3.1		4.95	0.000
	M	2.538	2.539	-0.2	92.6	-0.29	0.771
TEAM SIZE (LN)	U	0.80438	0.79077	2.2		3.52	0.000
	M	0.80435	0.80526	-0.1	93.4	-0.19	0.852
ORIGINALITY	U	0.66889	0.66261	2.5		4.07	0.000
	M	0.66888	0.66845	0.2	93.2	0.22	0.822
PATENT STOCK (LN)	U	0.59534	0.66002	-9.4		-15.51	0.000
	M	0.59536	0.59659	-0.2	98.1	-0.23	0.817
INDIVIDUAL	U	0.01807	0.01417	3.1		5.18	0.000
	M	0.01804	0.01849	-0.4	88.5	-0.43	0.665
BACKWARD CITATIONS (LN)	U	1.548	1.560	-2.1		-3.31	0.001
	M	1.548	1.543	0.8	62.3	1.00	0.317
COAPPLICANT	U	0.0665	0.04003	11.8		20.42	0.000
	M	0.06647	0.06504	0.6	94.6	0.75	0.456

Dummies for patent age, year of filing and technological fields are included in the probit model.

ing method we compute the standardized bias and we compare its size before and after the matching (Rosenbaum and Rubin, 1985). Table A-3 reports the mean and the median standardized bias, before and after the matching. Though there is no clear threshold under which it is possible to tell the success of the matching procedure with certainty, a bias reduction below 3 or 5 per cent is generally considered as sufficient (Caliendo and Kopeinig, 2008). As the Table shows, both the mean and the median standardized biases fall below the one per cent level after the matching, confirming the reliability of the matching on the propensity score.

Table A-3: Mean and median standardized bias for the matched and unmatched sample

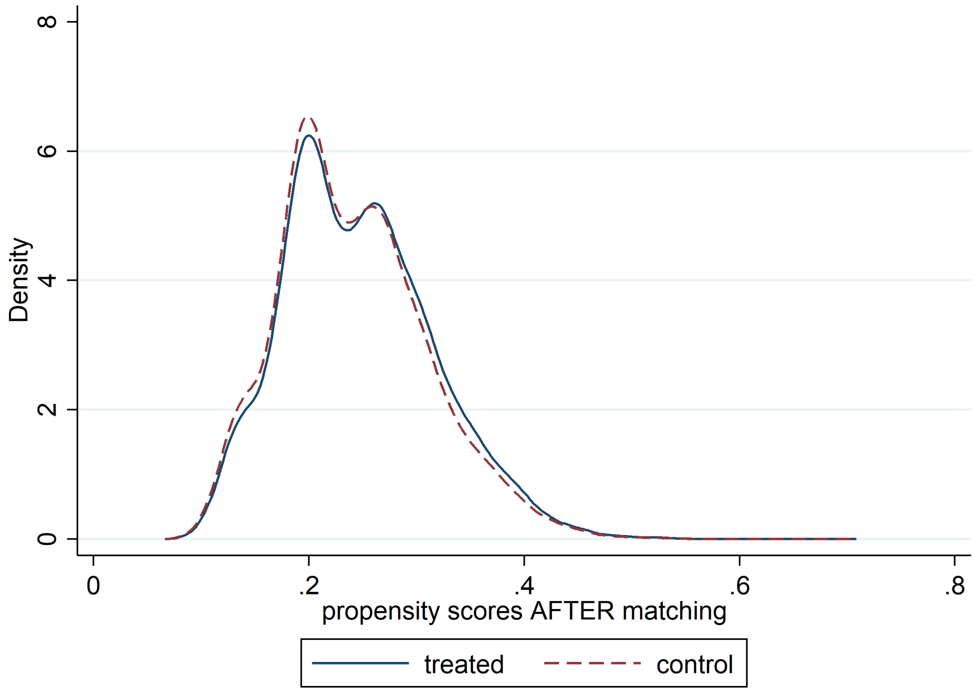
Sample	MeanBias	MedBias
Unmatched	4.3	2.8
Matched	0.3	0.2

The table reports the mean and the median standardized bias, before and after the matching.

Finally, since intuitively the matching procedure is implemented to “correct” for differences in terms of the probability of receiving the treatment between the treated and the control group, we can look at the visual representation of the propensity score distributions and make a comparison before and after the matching. As Figure A-2 displays, the difference in the Kernel density distribution of the estimated propensity scores abundantly diminishes with respect to the pre-matching situation offered by Figure A-1: the two distributions almost perfectly overlap, once again suggesting that the propensity score matching procedure successfully corrects for the selection on observable factors.

We present the results from the probit regression implemented for calculating the propensity scores in Table A-4. The probability of a patent being transferred is positively correlated with the average number of yearly citations it receives during the 4 years after the filing, with the number

Figure A-2: Kernel density distributions of the propensity score after the matching



of citations made, and with the dummy signaling for a co-applied patent. Conversely, a patent transfer is negatively correlated with the size of the applicant patent portfolio (*PATENT STOCK*): small entities are more likely than large entities to sell patents.

Table A-4: Probit results

	Coeff.	**SE**	**Z**
4Y FORWARD CITATIONS (LN)	0.0916***	0.0247	3.71
CLAIMS (LN)	0.0080	0.0063	1.26
TEAM SIZE (LN)	-0.0016	0.0061	-0.26
ORIGINALITY	0.0071	0.0176	0.40
PATENT STOCK (LN)	-0.0368***	0.0059	-6.25
INDIVIDUAL	0.0174	0.0295	0.59
BACKWARD CITATIONS (LN)	0.0340***	0.0076	4.51
COAPPLICANT	0.2696***	0.0167	16.12
Filing Year dummies	yes	.	.
Age dummies	yes	.	.
Technology dummies	yes	.	.
Country dummies	yes	.	.
Constant	-0.7347***	0.0256	-28.71
N		151,132	
Pseudo R^2		0.0270	

* $p < .1$, ** $p < .05$, *** $p < .01$.

A-3 Baseline models: Robustness checks

Table A-5: Baseline models (Exclusion of Self-Citations)

	(1) **No Self**	(2) **No Self**	(3) **No Self**	(4) **No Self**	(5) **No Self**
PE	0.070***	0.069***	0.048***	0.047***	
	(0.0030)	(0.0030)	(0.0029)	(0.0028)	
PAE	0.11***	0.14***	0.095***	0.088***	
	(0.023)	(0.028)	(0.027)	(0.027)	
TRADED	-0.041***	-0.040***	-0.015***	-0.015***	-0.012***
	(0.0030)	(0.0030)	(0.0029)	(0.0029)	(0.0022)
TRADED*PAE		-0.060**	-0.058**	-0.055**	-0.078***
		(0.026)	(0.026)	(0.026)	(0.022)
TEAM SIZE (LN)				0.056***	
				(0.0022)	
ORIGINALITY				0.078***	
				(0.0032)	
CLAIMS (LN)				0.084***	
				(0.0016)	
COAPPLICANT				0.026***	
				(0.0045)	
INDIVIDUAL				0.0014	
				(0.0073)	
PATENT STOCK (LN)				-0.0016	
				(0.0013)	
Age FE	Yes	Yes	Yes	Yes	Yes
Filing Year FE	No	No	Yes	Yes	No
Technology FE	No	No	Yes	Yes	No
Country	No	No	Yes	Yes	No
Patent FE	No	No	No	No	Yes
Observations	1,671,758	1,671,758	1,671,758	1,671,758	1,671,758
# of Patents	151,133	151,133	151,133	151,133	151,133
Adjusted R^2	0.035	0.035	0.067	0.081	0.384
F	193.1	145.5	127.1	208.4	22.7

All the models use the number of self-citation-excluded forward citations as the dependent variable (log transformed). Column (1) reports our most parsimonious estimation without our interaction of interest, with only patent age fixed effects included. In column (2) we add our interaction of interest. In column (4) we also control for a series of dummies: patent filing year, inventor's country of residence and technological domain. Column (4) includes the full set of covariates and is our preferred specification. Model in column (5) includes patent fixed effects. Clustered Standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$

Given the high share of PAEs' EP patents owned by INTERDIGITAL (see Table 2) and, importantly, due to the ambiguity of the company business definition,[49] we exclude those patents from the sample to ensure that our baseline results are not driven by one specific (possible) PAE's behavior. Once excluded those patents from the sample, we re-estimate our baseline model. Results are fully consistent with the ones presented in Table 8, and are presented in Table A-6.

Table A-6: Baseline models (Exclusion of INTERDIGITAL-acquired patents)

	(1) **Raw**	(2) **Raw**	(3) **Raw**	(4) **Raw**	(5) **Raw**
PE	0.039***	0.038***	0.018***	0.017***	
	(0.0032)	(0.0032)	(0.0031)	(0.0030)	
PAE	0.061**	0.087***	0.058**	0.047*	
	(0.024)	(0.029)	(0.028)	(0.027)	
TRADED	-0.023***	-0.023***	0.0027	0.0030	0.0086***
	(0.0031)	(0.0031)	(0.0031)	(0.0030)	(0.0022)
TRADED*PAE		-0.067**	-0.057**	-0.053**	-0.066***
		(0.027)	(0.027)	(0.027)	(0.023)
TEAM SIZE (LN)				0.069***	
				(0.0023)	
ORIGINALITY				0.084***	
				(0.0035)	
CLAIMS (LN)				0.095***	
				(0.0017)	
COAPPLICANT				-0.0063	
				(0.0047)	
INDIVIDUAL				-0.013*	
				(0.0075)	
PATENT STOCK (LN)				-0.00024	
				(0.0013)	
Age FE	Yes	Yes	Yes	Yes	Yes
Filing Year FE	No	No	Yes	Yes	No
Technology FE	No	No	Yes	Yes	No
Country	No	No	Yes	Yes	No
Patent FE	No	No	No	No	Yes
Observations	1,671,491	1,671,491	1,671,491	1,671,491	1,671,491
# of Patents	151,112	151,112	151,112	151,112	151,112
Adjusted R^2	0.033	0.033	0.065	0.081	0.403
F	51.1	39.7	92.4	193.7	10.5

We exclude patents acquired by Interdigital from the main sample. All the models use the raw number of forward citations as the dependent variable (log transformed). Column (1) reports our most parsimonious estimation without our interaction of interest, with only patent age fixed effects included. In column (2) we add our interaction of interest. In column (4) we also control for a series of dummies: patent filing year, inventor's country of residence and technological domain. Column (4) includes the full set of covariates and is our preferred specification. Model in column (5) includes patent fixed effects. Clustered Standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$

[49] https://www.ftc.gov/sites/default/files/documents/public_comments/2013/12/00048-87892.pdf

Table A-7: Baseline Models: Negative Binomial results

	(1)	(2)	(3)	(4)	(5)	(6)
	Raw	**Raw**	**Raw**	**No Appl**	**No Appl**	**No Appl**
PE	0.075***	0.067***	-0.021*	0.077***	0.072***	0.022
	(0.013)	(0.012)	(0.012)	(0.012)	(0.011)	(0.017)
PAE	0.23***	0.21***	0.51***	0.21**	0.19**	0.48***
	(0.082)	(0.082)	(0.11)	(0.081)	(0.080)	(0.15)
TRADED	0.042***	0.040***	0.051***	-0.0072	-0.0080	0.020***
	(0.015)	(0.015)	(0.0063)	(0.013)	(0.012)	(0.0069)
TRADED*PAE	-0.30***	-0.30***	-0.32***	-0.24**	-0.24**	-0.34***
	(0.11)	(0.11)	(0.060)	(0.12)	(0.11)	(0.066)
TEAM SIZE (LN)		0.33***			0.29***	
		(0.011)			(0.0098)	
ORIGINALITY		0.37***			0.35***	
		(0.019)			(0.017)	
CLAIMS (LN)		0.36***			0.36***	
		(0.0084)			(0.0074)	
COAPPLICANT		0.011			-0.018	
		(0.029)			(0.022)	
INDIVIDUAL		-0.021			-0.023	
		(0.047)			(0.035)	
PATENT STOCK (LN)		-0.0032			0.022***	
		(0.0068)			(0.0063)	
Age FE	Yes	Yes	Yes	Yes	Yes	Yes
Filing Year FE	Yes	Yes	No	Yes	Yes	No
Technology FE	Yes	Yes	No	Yes	Yes	No
Country	Yes	Yes	No	Yes	Yes	No
Patent FE	No	No	Yes	No	No	Yes
Observations	1,671,758	1,671,758	1,368,635	1,671,758	1,671,758	1318140

Negative binomial estimations. Models 1-3 estimate the effect on the raw count of forward citations. Models 4-6 use the count of applicant-excluded citations as the dependent variable. Models 1, 2, 4 and 5 include also age, filing, country and technology dummmies. Models 3 and 6 include patent fixed effects. Clustered Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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