On the Benefits of Cross-Firm Ownership for Cumulative Innovation

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December 12, 2019

Abstract

When innovation is cumulative, patent protection on early inventions can generate holdup problems if later complementary patents are owned by different firms. Consistent with the property rights literature, we show that shareholder ownership overlap across firms with patent complementarities helps mitigate such holdup problems and correlates significantly with higher R&D investment, more patent success, and lower patent infringement litigation risk for firms with follow-on innovations. The positive innovation effect is strongest for concentrated overlapping ownership and for the cases in which overlapping shareholders are dedicated investors, with long investment horizons and underdiversified portfolios.

JEL Classification: L22, G31, G32

Keywords: Patents, Holdup Problems, Innovation, Institutional Ownership

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1 Introduction

New technological discoveries often form part of a cumulative innovation process, in which later innovations build on a foundation provided by early innovators. Consequently, patent protection on early inventions implies that the full *economic* value of a later innovation might be unlocked only if the downstream (i.e., later) innovator can simultaneously secure access to many complementary upstream patents.[1] By law, when a follow-on product from the later innovator uses features that fall within the scope of protection of the first innovation, the second-generation innovator must obtain a license from the first-generation innovator, or risk being sued for patent infringement.[2] Viewed from this perspective, patent processes generate holdup problems for follow-on innovating firms whenever the complementary upstream patents are owned by different firms and ex-ante contracting is incomplete (and thus ex-post negotiations are needed).[3]

This paper gives a novel empirical perspective on the role of cross-firm equity ownership in attenuating patent holdup problems. Our research design follows a two-step procedure. First, following Galasso and Schankerman (2015), we use patent citation links to upstream firms to track cumulativeness in innovation and to proxy for the potential patent holdup risk faced by a downstream firm. Holdup expectations reduce a firm's ex-ante investment incentives, and costly patent rent extraction by upstream patent owners further results in ex-post inefficiency for the downstream firm. Second, we measure the cross-firm equity holdings by institutional investors in both the downstream innovating firm and the upstream firms that own complementary patents. From the property rights perspective of a firm (Grossman and Hart, 1986; Hart and Moore, 1990; Hart, 1995), such shareholder overlap should *extend the effective boundary of the downstream firm*, allowing for internalization of patent conflicts.

We document three main empirical results consistent with the holdup attenuation hypothesis of shareholder overlap. First, we find strong evidence that overlapping equity ownership across firms with complementary patents attenuates the R&D underinvestment problem and contributes to the patent success of the downstream innovating firm. A one-standard-deviation increase in

[1]Follow-on inventions can still be patented but they cannot be worked for *commercial* purposes if the follow-on products infringe on the patent rights of the earlier inventions.

[2]Lanjouw and Schankerman (2001) find evidence that upstream firms often file lawsuits to protect patents that form the base of a cumulative chain in order to extract rents from subsequent follow-on inventions.

[3]Anand and Khanna (2000) document that only about 14% of all licensing agreements occur ex ante. Williams (2013) documents a similar finding. These observations support the ex-ante incomplete contracting assumption.

firm-level shareholder overlap increases a downstream firm's average log forward patent citation count by 19% (10%) of its standard deviation (mean). It also coincides with an 11% higher R&D investment (relative to its mean) by the firm. All the results are robust to the use of the dollar value of a patent estimated by Kogan, Papanikolaou, Seru, and Stoffman (2017) as an alternative measure of patent success.

Second, regarding the transmission channel, we find evidence that the ownership overlap originating from the 25% most dedicated institutional investors (characterized by both low turnover and high concentration of their overall equity portfolios) shows a much stronger holdup attenuation effect. In addition, concentration of the shareholder overlap among a few large institutional investors strengthens the nexus between shareholder overlap and the patent success of the downstream firm. Furthermore, a one-standard-deviation increase in shareholder overlap is associated with a 19.8% reduction in patent litigation risk of the downstream innovating firms in our sample.

Third, we provide causal evidence based on a quasi-natural experiment where patent-level shareholder overlap increases exogenously due to a merger of financial institutions. We employ a difference-in-difference approach to compare the success of treatment and control patents. The post-merger treatment patents subject to financial institution mergers do indeed experience an economically significant increase in shareholder overlap at a magnitude of about 16.3% of its standard deviation, which is accompanied by a 3.9% increase in future citation count. Overall, the evidence from financial institution mergers points to an economically significant causal relationship of shareholder overlap on patent success. We also provide a variety of robustness tests to address omitted variable problems and deal with reverse causality concerns.

The theoretical literature on cumulative innovation (e.g., Heller and Eisenberg, 1998; Bessen, 2004; Bessen and Maskin 2009; Galasso and Schankerman, 2010, 2015) increasingly emphasizes the negative externalities early inventors might confer on later innovators. In general, when ex-ante contracting is incomplete, ex-post negotiation on the division of the downstream firm's patent revenue surplus is needed and such ex-post bargaining imposes two types of costs on the downstream firm, as highlighted in the transaction cost literature (Coase, 1937 and Williamson, 1975, 1985). First, time and effort spent in negotiating the ex-post division of surplus create ex-post inefficiencies for the downstream innovating firm because some of the resources are not put to productive use. Moreover, asymmetric information can lead to negotiation failure and subject the innovating firm to the risk of forgoing all its prior investment in the project (Galasso and Schankerman, 2015). Second, because the downstream innovating firm fears that it will not recover its investment costs due to a potential holdup (in the form of either complete negotiation failure or excessive royalty fees) by upstream patent owners, it underinvests in equilibrium, creating ex-ante inefficiencies for the firm (Hart, 1995).[4]

Only a few studies have empirically assessed the negative impact of patent rights on follow-on innovation. Williams (2013) reports that patent holdup reduces downstream research and product development by about 20%–30%. Her assessment is based on a case study of a single private firm called Celera. During the period 2001–2003, Celera owned essential intellectual property (IP) rights on the sequencing of genes. To extract rent from follow-on invention, Celera not only charged hefty fees for the use of its IP-protected data, but also demanded that downstream firms negotiate licensing agreements with the company for any consecutive commercial applications. Williams also documents that most of Celera's licensing agreements were negotiated ex post rather than ex ante. Ex-post negotiations weaken downstream innovators' bargaining positions as large proportions of their research costs have already been sunk at the time of negotiations. Murray and Stern (2007) and Galasso and Schankerman (2015) use patent citation data to track cumulativeness in innovation for a large sample. Murray and Stern (2007) exploit a setting in which a scientific article and a patent application co-exist on the same scientific finding by the same authors. They find robust evidence that the citation rate to a scientific article decreases by about 10%–20% after a patent is granted relative to the citation rate on articles without a related patent right. The evidence is consistent with the argument that upstream patent rights discourage scientists from building on prior knowledge developed by earlier innovators. Galasso and Schankerman (2015) explore a quasi-natural experiment that relies on patent invalidation in court. Overall, they find a 50% increase in citations of a focal patent after the patent is invalidated by the court. Again, upstream patent rights appear to impede follow-on innovations.

[4] See the detailed discussion in Hart (1995). In particular, even if ex-post negotiation is efficient (i.e., no haggling or asymmetric information), the innovating firm might still underinvest relative to the first-best scenario. Consider a simple example as follows: A downstream innovating firm A needs a patent license from its upstream firm B for commercialization of its own follow-on innovation. Assume that firm A's gross revenue from the innovation project is $R(i)$, which is concave and increasing in its ex-ante investment i, and that the total cost of producing the upstream firm's patent is C, which was incurred prior to the start of firm A's patent project and is independent of i. Further assume that without the patent license from firm B, firm A would realize zero gross revenue. In the first-best world, the optimal investment i^* solves the problem of $R'(i) = 1$. Now, suppose firm A expects ex-post bargaining to result in a 50:50 split of ex-post gains between the two firms (by Nash bargaining). Firm A would optimally choose an investment level i^{**} that solves the problem of $\frac{1}{2}R'(i) = 1$; that is, underinvestment occurs ($i^{**} < i^*$). A more complete theoretical model is presented in Geng, Hau, and Lai (2017).

Our paper contributes to this strand of the literature by exploring how ex-ante variations in cross-firm ownership (as de facto extensions of the firm ownership boundary) affect the patent holdup problem. We hypothesize that overlapping shareholders might have incentives to internalize patent conflicts between upstream and downstream firms so as to maximize their overall portfolio value.[5] To subject our hypothesis to a systematic empirical examination, we combine a large sample of U.S. patent data from the United States Patent and Trademark Office (USPTO) with institutional ownership data from Thomson Reuters for the period 1991–2007. In particular, we track stock ownership not only for the innovating firms, but also for firms owning complementary patents. We follow Murray and Stern (2007) and Galasso and Schankerman (2015) to track cumulativeness in innovation directly from patent filings that explicitly list important upstream patents owned by other firms. By law, each newly filed patent must list prior art references (i.e., upstream patents) that are technologically related and material to the patentability of the new application. Although inventors have a duty of candor to disclose all material prior art, patent examiners in USPTO are officially responsible for constructing the list of references. According to Alcácer, Gittelman, and Sampat (2009), examiners insert at least one citation in 92% of patent applications, and examiner citations account for about 63% of all citations made by an average patent. Our analysis identifies potential patent holdup based on this list of prior art references and assumes that the list is exogenously determined by the technology to be patented. Indeed, the frequent addition of precursory patents by patent examiners suggests that the patent-filing firms have limited scope to manipulate the reference list.

Prior research (Ziedonis, 2004; Noel and Schankerman, 2013; and Galasso and Schankerman, 2015) suggests that owners of upstream cited patents are reasonable proxies for the potential licensors of downstream citing patents. So-called patent-consultants have occasionally disclosed that they screen the list of companies that cite their clients' patents to identify potential licensees (Ziedonis, 2004).[6] In fact, two U.S. inventors, Stephen K. Boyer and Alex Miller, were granted a patent (US6879990) in 2005 for proposing a systematic approach to identifying potential licensees

[5] It's noted that shareholder overlap amounts to partial integration of two firms. Although firms might also seek outright ownership integration via mergers to resolve patent disputes, firm mergers involve high transaction costs and might be challenged in court for anti-competitive reasons (Creighton and Sher, 2009). We argue that in liquid equity markets, partial ownership integration via shareholder overlap might be achieved at lower costs.

[6] Ziedonis (2004) discussed three cases in her paper (Mogee Associates, InteCap, and Delphion). Ambercite, another intellectual property consulting company, advocated a similar approach in a recent internet posting (www.ambercite.com, 2014).

from patent citation references.[7] Commenting on the strength of the citation measure, Galasso and Schankerman (2015) state that "*From an economic perspective, patent citations play two distinct roles: they indicate when a new invention builds on prior patents (and thus may need to license the upstream patent), and they identify prior art that circumscribes the property rights that can be claimed in the new patent.*" Following this line of literature and industry practice, our analysis uses patent citation links to upstream firms to track cumulativeness in innovation and to proxy for the potential patent holdup risk faced by a downstream firm.

Two new databases provide evidence that supports the quality of this proxy. Data from Audit Analytics Litigation show in Figure 1, Panel A, that firms with citation links are on average 15 times as likely to engage in patent-related lawsuits against each other as those without any citation links.[8] For a subset of firms in the pharmaceutical industry, we are also able to obtain licensing deals and royalty transfer information from the Cortellis database.[9] Panels B and C in Figure 1 show that firm pairs with citation links feature 17.9 times more licensing deals and 43.6 times more royalty transfer between each other than firm pairs without citation links. Overall, the data on patent litigation, licensing deals, and royalty transfer support the argument that citation links represent a reasonable proxy for asset complementarity and patent holdup risk.

In our empirical strategy, we exploit the fact that even in the same downstream firm, different patents might build on different sets of precursory patents and are therefore subject to different degrees of patent holdup risk. We first construct a new variable, *pairwise shareholder overlap* ($PSOL$), which is the minimum ownership share that investors own jointly in the downstream innovating firm and an upstream firm controlling a complementary patent. Consider a patent p owned by a downstream firm $O(p)$) that cites a precursory patent p_u owned by an upstream firm

[7] They suggest creating a pool of associated patents from citation references of the target patents. Certain weighting scheme and ranking criteria are then applied to rank the owners of these associated patents to identify companies that are most likely to need a patent license from the target firms.

[8] The Audit Analytics Litigation database collects data primarily from corporate disclosures to the Securities and Exchange Commission (SEC). Reported are 604 patent lawsuits over the period 2000–2007. Although these lawsuits may represent only a subset of all patent lawsuits, we are not aware of any reporting bias toward firm pairs with or without citation links. The existing literature, such as Cohen and Gurun (2018), has also employed this database to carry out litigation-related analysis.

[9] Our analysis includes only the licensing deals of which both the licensor and licensee are included in the CRSP database. The final sample comprises a total of $1,238$ licensing deals for the period 1991–2007. We count the number of licensing deals in which the licensee cited the licensor in the past three years. We then calculate the aggregate royalties in these deals. We also count the number of licensing deals and royalty value for firm pairs without any citation links in the past three years. Although royalties generally increase with the importance of a patent (Sichelman, 2018), the Cortellis database does not indicate which exact patent(s) is (are) covered in each licensing deal.

$O(p_u)$. If two investors A and B, respectively, own 3% and 5% in the downstream firm $O(p)$, and 2% and 6% in the upstream firm $O(p_u)$, their combined shareholder overlap for the patent pair (p, p_u) amounts to 7% [$= min(3\%, 2\%) + min(5\%, 6\%)$]. The *patent-level shareholder overlap* (sol) follows by averaging over all upstream patents cited in the patent filing of patent p, and the *firm-level shareholder overlap* (SOL) is obtained by jointly averaging over all patents of the downstream innovating firm and their respective upstream patents.

Following the literature (e.g., Aghion, Van Reenen, and Zingales, 2013; Acharya and Xu, 2017; and Blanco and Wehrheim, 2017), we measure patent success by the forward citation count $cites_{p,t}$ of each patent p that is filed in year t and subsequently granted. Overall firm-level patent success is denoted as $CITES_{s,t}$, which aggregates all future patent citations of the entire cohort of patents filed by firm s in year t. Forward citation count has been shown to correlate positively with the economic value of a patent (e.g., Harhoff, Narin, Scherer, and Vopel, 1999; Kogan et al., 2017) and with firm value (e.g., Hall, Jaffe, and Trajtenberg, 2005; Farre-Mensa, Hegde, and Ljungqvist, 2018). We also use the dollar value of a patent estimated by Kogan et al. (2017) as an alternative measure of patent success and find qualitatively similar results.[10]

Our paper continues as follows. Section 2 surveys the related literature, and Section 3 describes the data. Section 4 provides supportive evidence for the holdup attenuation hypothesis, Section 5 subjects the transmission channel to various plausibility tests, and Section 6 provides causal evidence that shareholder overlap influences patent success. More robustness considerations follow in Section 7, and Section 8 concludes.

2 Related Literature

The early literature on cumulative (or sequential) innovation emphasizes a positive externality of early innovators on later innovators via knowledge spillovers (e.g., d'Aspremont and Jacquemin, 1988). A seminal paper by Green and Scotchmer (1995) argues that in a perfect contracting environment, ex-ante licenses are optimal and will be negotiated. In their framework, efficient

[10] Although forward citation count is an indirect measure of patent success, it has the advantage that it is directly observable for a large number of firms with a long history. The measure used in Harhoff et al. (1999) is based on a survey conducted in 1999 and is available for only a small number of U.S. and German patents. The precision of the dollar values of patents estimated by Kogan et al. (2017) relies on the validity of the model assumptions they use to obtain the estimates. Among other things, they assume that investors have perfect knowledge about the market value of a patent before it is granted by USPTO. Any violation of the model assumptions can cause the estimates to deviate away from their true values.

bargaining ensures that upstream patent rights do not impede follow-on innovation. More recent studies (e.g., Heller and Eisenberg, 1998), however, argue that various transaction costs exist and can result in inefficient bargaining and patent holdup risk for downstream innovators. Bargaining failure due to information asymmetry (Bessen and Maskin 2009; Galasso and Schankerman 2015) and/or excessive royalty stacking (Galasso and Schankerman, 2010) can even block follow-on innovation entirely. Empirically, Murray and Stern (2007), Williams (2013), and Galasso and Schankerman (2015) find evidence that patent holdup reduces downstream research and development by about 10%–50%. Lanjouw and Schankerman (2001) further document the litigation risk faced by downstream innovators as upstream patent owners try to maximize their overall patent rents. In particular, upstream firms are more likely to file infringement lawsuits to protect patents that form the base of a cumulative chain and patents that are cited by more follow-on patentees. Our paper contributes to this strand of the literature by exploring how ex-ante variations in cross-firm ownership affect the patent holdup problem.

The property rights literature (Grossman and Hart, 1986; Hart and Moore, 1990; Hart, 1995) suggests that *joint asset ownership* attenuates holdup problems under conditions of *asset specificity* and *ex-ante incomplete contracting*. In the case of cumulative innovation, the first condition (asset specificity) is fulfilled for many new downstream patents because by law a downstream innovating firm must license upstream patents before it can market its follow-on (or second generation) products that use features under the IP protection of upstream patents. The second condition (ex-ante incomplete contracting) is also fulfilled. Various contingencies can arise during an innovation process. The randomness of the outcome of any innovation project makes it impossible for an innovating firm to write an ex-ante complete contract. The need for ex-post negotiation thus creates a patent holdup problem for the downstream firm.

Notwithstanding its prominence in economic theory, the property rights view of firm boundaries has seen few empirical applications. A variety of empirical problems explains the scarcity of evidence. First, *non-contractible holdup problems* are often difficult to identify in a complicated business environment. Second, *underinvestment at the project level* requires a level of data disaggregation typically not available from corporate investment data, and any firm-level analysis is clouded by the fact that a firm can shift investments to other projects for which holdup problems are less severe. Third, investments may involve intangible resources (such as managerial attention), which pose additional *measurement problems* for empirical analyses. In this study, we overcome various empirical difficulties. First, we identify the potential patent holdup risk directly through the explicit citation of precursory patents in patent filings. Second, we infer (latent) underinvestment in a patent project indirectly from the diminished success of the patent. Aggregate firm-level underinvestment is inferred directly from the reported firm-level R&D expenditure (or indirectly from the diminished success of all patents filed by a firm). Third, we measure the success of a patent project using forward citation count or the estimated dollar value of the patent.

Our work is also related to a growing literature on the coordination role of common (or overlapping) shareholders in corporate policies. Since Rubinstein and Yaari (1983) and Rotemberg (1984), a number of theoretical studies have argued that overlapping shareholders might coordinate to reduce competition in product markets. Schmalz (2018) gives a thorough review of the literature. Recent empirical studies provide evidence consistent with this theoretical prediction. In particular, Azar, Schmalz, and Tecu (2018) show that overlapping ownership softens product market competition in the U.S. airline industry. Similar evidence is also documented by Aslan (2019) for the consumer goods industry and by Newham, Seldeslachts, and Estañol (2019) and Gerakos and Xie (2019) for the pharmaceutical industry. He and Huang (2017) also show that large overlapping shareholders facilitate product market collaboration among their portfolio firms in the same industry, and that these firms experience greater profitability and market share growth.[11] Our paper is not concerned with shareholder overlap per se, but with its relevance and potency in the specific setting of patent holdup in cumulative innovation processes. In other words, we focus on a much more specific setting central to the microeconomic theory of the firm.

Recent empirical work has also highlighted the complementarity between equity market development and the degree of patent innovation (Brown, Martinsson, and Petersen, 2013, 2017; Hsu, Tian, and Xu, 2014). Insofar as equity market development allows for better internalization of holdup problems (through enhanced and adjustable *shareholder overlap*), this paper offers a deeper microeconomic interpretation rooted in the theory of the firm for the documented findings.

[11] López and Vives (2019) and Anton, Ederer, Giné, and Schmalz (2018) argue that overlapping ownership between rival firms on the one hand mitigates these firms' R&D disincentives caused by the free-riding problems in the presence of technological spillover, but on the other hand softens product market competition, which in turn reduces these firm's R&D incentives. Shradha (2019) finds that for firms operating in industries with similar products, overlapping ownership does indeed lead to less R&D investment. In contrast, our study predicts and finds a positive relation between a downstream firm's R&D investment and its overlapping ownership with upstream firms that own complementary patents.

3 Data

3.1 Patent Information

We collect patent and citation information from the data set provided by Kogan et al. (2017). The data set contains annual patent and citation information for patents granted over the period 1926–2010.[12] Following the existing literature (e.g., Aghion et al., 2013; Acharya and Xu, 2017; Blanco and Wehrheim, 2017), we use the total number of a patent p's future citations ($cites_{p,t}$) from the patent filing year t to 2010 as our proxy for patent success. Generally, a patent is not known to the public during its application stage until USPTO publishes it, typically 18 months after the filing date. For earlier patents (filed before November 29, 2000), patent applications are not published until after they are granted. According to Hall, Jaffe, and Trajtenberg (2001), it takes on average 18 months for a patent's application to be approved and about 95% of successful patent applications are granted within three years of application.

We aggregate the patent-level count statistic $cites_{p,t}$ to the total number of future citations generated by the cohort of patents filed by firm s in year t, denoted by $CITES_{s,t}$. Self-citations are excluded. Following the convention in the innovation literature (e.g., Acharya and Xu, 2017), we set the citation count of a patent to zero when there is no citation information provided in the data. For firms without any patents, we set their total citation count to missing. We also examine the extensive margin of patent production $N_{s,t}$, defined as the number of patent filings by firm s in year t. The corresponding intensive margin is measured by the average citations per patent $\overline{cites}_{s,t}$ (which equals the ratio of $CITES_{s,t}$ to $N_{s,t}$). Because most of these patent-related measures are highly skewed, we generally apply a log transformation $ln(1 + X)$ to obtain more normally distributed variables for regression analyses.

We follow standard procedures to adjust for patent and citation truncation biases. First, because the patent data set only includes those patents that are eventually granted, we use only patent applications up to 2007 in our empirical analysis to allow for a three-year window of future citations up to 2010. Second, we control for year fixed effects in all regressions to account for the fact that earlier cohorts of patents have more time to be cited than later cohorts. Third, we adjust for patent citation count based on the shape of the citation-lag distribution suggested by

[12] The data set is available at https://iu.app.box.com/patents. We thank Professor Noah Stoffman for making the data set available to us.

Hall et al. (2001, 2005).[13] Fourth, we also perform our tests using simple (unweighted) patent counts (i.e., extensive margin reported in Section 4.2). Fifth, as a robustness check, we count only the citations received during the calendar year of the patent grant and three subsequent years (Lerner, Sørensen, and Strömberg, 2011). Note also that because expired patents would not create any holdup problems, we ignore upstream patents that have expired by the time the shareholder overlap measure is constructed.[14]

3.2 Ownership Data

We obtain the ownership data from the Thomson Reuters 13F database. The SEC requires all institutional organizations, companies, universities, etc., that exercise discretionary management of investment portfolios over $100 million in equity assets to report their holdings on a quarterly basis. All common stock positions greater than 10,000 shares or $200,000 must be reported. Aghion et al. (2013) show reporting inconsistencies in ownership data prior to 1991, so we use ownership data only from 1991 onwards.

We then combine the patent and citation data with institutional ownership data for publicly listed firms in the United States. The control variables, including the (log) total assets $ln(Assets_{s,t-1})$, cumulative R&D investment $ln(1+R\&D\ Stock_{s,t-1})$, capital intensity $ln(K/L_{s,t-1})$, and firm leverage $leverage_{s,t-1}$, are drawn from the Compustat database and are chosen based on the existing literature (e.g., Aghion et al., 2013; Lin, Liu, and Manso, 2019). Following the general practice in the finance literature (e.g., Bloom, Schakerman, and Van Reenen, 2013; and Koh and Reeb, 2015), we set R&D expenditure to zero if it is not reported in the Compustat database, and we include in our regression models a dummy variable of 1 for the firm-year observations with missing R&D data. We obtain qualitatively similar results if we drop the missing R&D values or interpolate their values for any gaps of no more than three years. Lastly, we exclude all firm-year observations with missing values for the explanatory or control variables. Our final sample features $2,893$ U.S. publicly listed firms over the sample period 1992–2007, with a total of $582,694$

[13] For example, for a chemical patent filed in 2000, we observe only 10 years of citations. According to Table 5 of Hall et al. (2001), for a typical chemical patent about 52.9% of the estimated total citations occur during the first 10 years. Therefore, we would divide the observed total by 0.529 to yield the truncation-adjusted total citations.

[14] According to USPTO, the 20-year protection period for utility patents starts from the grant date and ends 20 years after the patent application was first filed. The only exception applies to those patents that are filed before June 8, 1995; these patents have a protection period that is the greater of either the 20-year term discussed earlier or 17 years from the grant date (http://www.uspto.gov/web/offices/pac/mpep/mpep-2700.pdf).

patents and 18,763 firm-years of patent production.

3.3 Variable Construction

A key explanatory variable in our analysis is *shareholder overlap*, which we define as follows: Let $O(p)$ designate the downstream innovating firm owning patent p and $O(p_u)$ represent the upstream firm owning patent p_u. The *pairwise (institutional) shareholder overlap* between the downstream patent p and an upstream patent p_u is defined as

$$PSOL(p, p_u) = \sum_i \min[w_{i,O(p)}, w_{i,O(p_u)}], \tag{1}$$

where $w_{i,O(p)}$ and $w_{i,O(p_u)}$ are the ownership share (relative to the total institutional ownership of the respective firm) of institutional investor i in firms $O(p)$ and $O(p_u)$, respectively. We lag the ownership measure by one year relative to the application year of patent p. The *patent-level shareholder overlap* (sol) follows as the average of $PSOL(p, p_u)$ over the N_u upstream patents of patent p, given by

$$sol_p = \sum_{u=1}^{N_u} \frac{1}{N_u} PSOL(p, p_u). \tag{2}$$

The *firm-level shareholder overlap* (SOL) is obtained by averaging sol_p over all N_p patents filed by firm s in a given year, given by

$$SOL_s = \sum_{p=1}^{N_p} \frac{1}{N_p} sol_p = \sum_{p=1}^{N_p} \sum_{u=1}^{N_u} \frac{1}{N_p} \frac{1}{N_u} PSOL(p, p_u). \tag{3}$$

A limitation of our analysis is that due to data constraints we can measure ownership only for publicly listed firms, not for private firms. Neither are data on the portfolio holdings of private investors generally publicly available. As a result, we may underestimate the extent of shareholder overlap, especially when the proportion of privately owned upstream patents is large. This imprecise measure of shareholder overlap creates an attenuation bias in the OLS estimate of SOL. To mitigate this effect, we track the average share of privately owned upstream patents for each downstream firm s and include it as a control variable, denoted by *Private Patent Share*$_s$.

3.4 Summary Statistics

Institutional ownership in U.S. listed stocks has grown rapidly, from an average of 25% in 1991 to 49% in 2006. The corresponding share is considerably larger for patent-filing firms and rises from 41% in 1991 to 71% in 2006. Patent-filing firms tend to be larger, and institutional investors typically prefer large firms. Parallel to the rise in institutional ownership, the average firm-level shareholder overlap increases from 15.7% in 1991 to 22% in 2006. In our analysis, year fixed effects are included in all regressions to ensure that the documented shareholder overlap effect does not capture any parallel time trend in patent success. Cross-sectionally, shareholder overlap is positively related to institutional ownership, but it also varies substantially across firms with similar levels of institutional ownership. Such large heterogeneity in a firm's indirect control over complementary upstream patents via overlapping shareholders could plausibly condition patent holdup and determine a firm's long-run patent success.

Table 1 reports the summary statistics of the key variables used in our analysis. Patent-level shareholder overlap (sol) shows an average of 26.9% with a standard deviation of 16%, much larger than the corresponding statistics of 17.2% and 12% for firm-level shareholder overlap (SOL). The higher mean and standard deviation for the former are explained by the fact that firms with many patent filings are usually larger and feature a higher level of shareholder overlap. A median firm in our sample has about four patents and 49 (citation-lag adjusted) forward citations, with an aggregate estimated patent value of about 8 million in 1982 dollars per year.[15] Detailed definitions of all variables are provided in Appendix A.

4 Evidence on Holdup Attenuation

4.1 Baseline Specification

Our main hypothesis is that joint equity ownership between the downstream innovator and the upstream firms controlling complementary patents attenuates the holdup problem and contributes to the patent success of the downstream innovating firm. Our baseline regression links a firm's patent success [measured in log terms as $ln(1+CITES_{s,t})$] to shareholder overlap (at the end of

[15] As discussed in Kogan et al. (2017), their estimates of patent values are somewhat higher than those estimated by inventors themselves in a survey reported in Giuri et al. (2007). However, these estimates are still useful in cross-section and time-series comparisons of patent values.

period $t-1$) in the following linear regression

$$ln(1 + CITES_{s,t}) = \beta_0 + \beta_1 SOL_{s,t-1} + \beta_2 Controls_{s,t-1} + \epsilon_I + \mu_t + \eta_{s,t}, \tag{4}$$

where the coefficient of interest β_1 is predicted to be positive if the firm's shareholder overlap ($SOL_{s,t-1}$) with complementary upstream patent owners attenuates holdup. The baseline regression is estimated for the period 1992–2007. The citation count $CITES_{s,t}$ for patents filed by firm s in year t includes all future citations up to year 2010, which are adjusted for the shape of the citation-lag distribution following Hall et al. (2001, 2005). For the choice of control variables, we follow Aghion et al. (2013) and Lin et al. (2019) to include the (log) total assets $ln(Assets_{s,t-1})$, the cumulative R&D investment $ln(1 + R\&D\ Stock_{s,t-1})$, a measure of relative capital intensity $ln(K/L_{s,t-1})$, and firm leverage $leverage_{s,t-1}$. We also control for the share of private firms in the cited upstream firms, $Private\ Patent\ Share_{s,t-1}$, and include industry and year fixed effects ϵ_I and μ_t.

Table 2, Columns 1–2 present the results with robust standard errors clustered at the firm level reported in parentheses. All regressions control for a full set of year dummies and industry dummies based on four-digit SIC codes. Column 2 also controls for firm fixed effects, using the Blundell, Griffith, and Van Reenen (1999) pre-sample mean scaling estimator.

The ordinary fixed effect estimator with firm dummies is inconsistent if the independent variables (such as SOL) are only predetermined rather than being strictly exogenous (Imbens and Wooldridge, 2007).[16] Blundell et al. (1999) propose a "pre-sample mean scaling" method to control for firm fixed effects and show that this estimator remains consistent even with predetermined regressors. This approach essentially replaces firm dummies with the pre-sample mean of the dependent variable (measured at the firm level). To make sure our regression estimates are consistent, we follow this procedure and construct a 25-year pre-sample mean of $CITES_{s,t}$.[17] The same procedure is also employed by Blundell et al. (1999) to examine the relation between innovations and market shares, by Aghion et al. (2013) to examine the relation between innovations and institutional ownership, and by Blanco and Wehrheim (2017) to examine the relation between

[16] The asymptotic bias is especially large for samples with small T. Specifically, Imbens and Wooldridge (2007) show that under contemporaneous exogeneity the fixed effect estimator with firm dummies has the property: plim $\hat{\beta} = \beta + O(T^{-1})$.

[17] For firms with fewer than 25 years of pre-sample history, we use the maximum number of years available to calculate the pre-sample mean. We require firms to have at least one year of pre-sample history to be included in the sample. Using an alternative cutoff of 20, 15, or 10 years does not change our results qualitatively.

innovations and option trading.

The baseline regression in Column 1 shows that shareholder overlap represents a statistically and economically significant explanatory variable with the predicted positive coefficient. The coefficient remains highly significant in Column 2, where we control for firm fixed effects as suggested by Blundell et al. (1999). A point estimate of 3.234 for SOL implies that an increase in shareholder overlap by one standard deviation (or 0.120) increases patent success in terms of a firm's log patent citation [$ln(1{+}CITES)$] by 19% of its standard deviation (2.071) or 10% of its mean (3.948). This shows that shareholder overlap with upstream firms owning complementary patents correlates strongly with the patent success of the downstream firm—a finding supportive of the holdup attenuation hypothesis.

4.2 Intensive versus Extensive Margins

The previous section explored the link between holdup attenuation and overall patent success. However, shareholder overlap can affect the intensive and extensive margins differently. The intensive margin of patent success is captured by the average number of citations per patent, $\overline{cites}$. Again, we use the logarithmic transformation $ln(1+\overline{cites}_{s,t})$ to obtain a suitable dependent variable for the linear regression

$$ln(1+\overline{cites}_{s,t}) = \theta_0 + \theta_1 SOL_{s,t-1} + \theta_2 Controls_{s,t-1} + \epsilon_I + \mu_t + \eta_{s,t}, \tag{5}$$

where $\theta_1 > 0$ implies that shareholder overlap correlates with greater long-run success of each patent filed. A positive value of θ_1 also points to ex-post patent value destruction if patent conflict is not attenuated through shareholder overlap. Geng et al. (2017) provide a theoretical model of this. Table 2, Columns 3–4 summarize the relationship between shareholder overlap and the intensive margin of patent success. The point estimate (1.132) in Column 4 implies that an increase in shareholder overlap by one standard deviation (or 0.12) corresponds to an increase in the average citation count per patent of about 12% (6%) of its standard deviation (mean) of 1.145 (2.385).

The analogous specification for the extensive margin uses the (log) number of granted patents [$ln(1+N_{s,t})$] for firm s in year t as the dependent variable in the linear regression

$$ln(1+N_{s,t}) = \psi_0 + \psi_1 SOL_{s,t-1} + \psi_2 Controls_{s,t-1} + \epsilon_I + \mu_t + \eta_{s,t}, \tag{6}$$

where the coefficient ψ_1 captures the relation between shareholder overlap ($SOL_{s,t}$) and the (log) number of granted patents. Table 2, Column 6 again reports a positive point estimate given by $\widehat{\psi}_1 = 1.733$. A one-standard-deviation increase in SOL is associated with a 21% increase in the number of patents—suggesting an economically strong nexus between holdup attenuation and the number of successful patent filings.

Overall, the results suggest that holdup attenuation through shareholder overlap is associated both with more citations for each patent granted (i.e., the intensive margin of patent success) and the pursuit of more patent filings (i.e., the extensive margin of patent production). The latter effect is of particularly high economic significance, indicative of a severe underinvestment problem related to patent holdup in cumulative innovation processes. We explore this issue further in the next section by examining the relation between shareholder overlap and R&D investment.

4.3 R&D Investment

The holdup attenuation hypothesis implies that shareholder overlap should not only foster patent success, but also reduce ex-ante firm underinvestment in R&D. R&D expenditure is directly reported and thus provides a useful accounting statistic to assess firm-level inputs into the patent development process.

We regress a firm's R&D expenditure relative to assets ($R\&D\ Exp_{s,t}/Assets_{s,t}$) on its shareholder overlap ($SOL_{s,t-1}$) with relevant upstream firms owning complementary patents using the following linear specification

$$R\&D\ Exp_{s,t}/Assets_{s,t} = \kappa_0 + \kappa_1 SOL_{s,t-1} + \kappa_2 Controls_{s,t-1} + \epsilon_s + \mu_t + \eta_{s,t}, \tag{7}$$

where the control variables include the (log) total assets $ln(Assets_{s,t-1})$, relative capital intensity $ln(K/L_{s,t-1})$, firm leverage $leverage_{s,t-1}$ and $Private\ Patent\ Share_{s,t-1}$. We also control for firm and year fixed effects ϵ_s and μ_t. Table 3, Column 1, reports a statistically highly significant point estimate of 0.117 for shareholder overlap. An increase in shareholder overlap by one standard deviation (or 0.120) increases the R&D expenditure to asset ratio by roughly 7% of its standard deviation (0.213) or about 11% of its mean (0.123). This suggests that the holdup attenuation effect of shareholder overlap on R&D investment is economically important.

Previous research has argued that institutional ownership can *ceteris paribus* provide better long-term managerial incentives conducive to the pursuit of R&D (e.g., Aghion et al., 2013). We therefore control for institutional ownership in Column 2, but find that the shareholder overlap variable (SOL) retains its economic and statistical significance, whereas the institutional ownership variable (IO) is statistically insignificant. To probe this issue further, we decompose institutional ownership itself into (i) ownership by overlapping institutional shareholders (IO^{SOL}) that contributes to shareholder overlap (i.e., the aggregate ownership of all shareholders i with $\min[w_{i,O(p)}, w_{i,O(p_u)}] > 0$ for at least one downstream-upstream patent pair (p, p^u)); and (ii) residual non-overlapping institutional ownership (IO^{NOL}). Formally, for each downstream firm s in year t we have

$$IO_{s,t} = IO_{s,t}^{SOL} + IO_{s,t}^{NOL}. \tag{8}$$

By construction, IO^{SOL} strongly correlates with the shareholder overlap measure SOL, with a correlation of 0.53 during our sample period. If institutional ownership *per se* exerts a positive influence on R&D investment, we expect the same positive coefficient for both $IO_{s,t-1}^{SOL}$ and $IO_{s.t-1}^{NOL}$ in our regressions. Column 3 modifies the specification in Eq. (7) to include both overlapping institutional ownership $IO_{s,t-1}^{SOL}$ and non-overlapping institutional ownership $IO_{s.t-1}^{NOL}$ and reveals that the effect is significant only for overlapping institutional owners.

5 Transmission Channels

Which type of overlapping shareholders has the strongest incentives to resolve a potential patent holdup and the greatest ability to influence corporate managers in the resolution of holdup? First, long-term institutional investors with concentrated portfolio positions might devote more time and effort to resolving patent-related conflicts. Second, concentration of overlapping ownership among relatively few institutional investors might limit free-riding and facilitate the coordination of investor influence. Next, we isolate these two dimensions of shareholder overlap and show that they determine the strength of the holdup attenuation in patent processes. We then further investigate the effect of shareholder overlap on an innovating firm's patent infringement litigation risk.

5.1 Dedicated Shareholder

To test the first hypothesis, we categorize institutional investors into (i) dedicated investors and (ii) non-dedicated investors based on a *combination* of portfolio concentration (proxied by the Herfindahl-Hirschman Index, HHI) and portfolio turnover (proxied by the churn ratio defined in Gaspar, Massa, and Matos, 2005). At the end of each year, we sort all institutional investors by the HHI (in descending order) and churn ratio (in ascending order). We label investors in the top 50% of both the HHI sort and the churn ratio sort (i.e., high concentration and low turnover) as dedicated investors and the remaining investors as non-dedicated investors. We decompose the overall shareholder overlap into parts coming from either dedicated investors or non-dedicated institutional investors, i.e.

$$SOL_{s,t-1} = SOL\_Ded_{s,t-1} + SOL\_NonDed_{s,t-1}, \tag{9}$$

and repeat the regressions in Table 2, Column 2, with both disaggregated explanatory variables.

Table 4, Column 2, reports the results and confirms the hypothesis that dedicated (overlapping) investors matter the most for holdup attenuation. The shareholder overlap contributed by dedicated investors (SOL_Ded) features a coefficient of 9.768 compared to the baseline coefficient of 3.24 for all shareholder overlap (reported again in Column 1 of Table 4). We can reject the null hypothesis that dedicated and non-dedicated shareholder overlap make the same contribution to patent success measured in terms of future patent citations [$ln(1 + CITES_{s,t})$].[18]

5.2 Concentration of Shareholder Overlap

The second hypothesis concerns the concentration of shareholder overlap. To test this hypothesis, we consider a downstream patent p filed by firm s in year t and a related upstream patent p_u owned by firm u. Let $i \in I_{(p,p_u),t-1}$ denote an overlapping investor, who at the end of time $t-1$ owns equity shares (relative to total institutional ownership) $w_{i,s}$ and $w_{i,u}$ in firms s and u, respectively. For a patent pair (p, p_u), we can define a Herfindahl-Hirschman Index ($hhi_{(p,p_u),t-1}$) based on the

[18] How can long-term, dedicated investors influence corporate decisions? In a survey of institutional investors, McCahery, Sautner, and Starks (2016) document that long-term, dedicated investors intervene more frequently than short-term investors. They do so mainly through private, behind-the-scene discussions with management and private meetings with corporate board members. In addition, they discipline management with threats of exit, which they view as a complement to direct intervention. Crane, Koch, and Michenaud (2019) also find evidence that institutional investors coordinate and vote together against low-quality management proposals to improve corporate governance of their portfolio firms.

overlapping ownership shares $\varpi_i = \min[w_{i,s}, w_{i,u}]$ of all overlapping shareholders $i \in I_{(p,p_u),t-1}$. We can further average this concentration measure $hhi_{(p,p_u),t-1}$ over all N_u upstream patents (p_u) related to patent p and, subsequently, over all N_p downstream patents (p) filed by firm s in year t to obtain an average Herfindahl-Hirschman Index ($SOL\_HHI_{s,t-1}$) of ownership concentration of overlapping shareholders, defined as

$$SOL\_HHI_{s,t-1} = \sum_{p=1}^{N_p} \sum_{u=1}^{N_u} \frac{1}{N_p} \frac{1}{N_u} hhi_{(p,p_u),t-1}, \tag{10}$$

where ownership shares are measured at the end of year $t-1$. SOL_HHI describes the concentration of overlapping ownership stakes at the firm level and thus captures the coordination problem among overlapping shareholders.

Table 4, Column 3 includes SOL_HHI as a separate control variable. The estimated coefficient is positive and statistically highly significant—suggesting that concentration of joint ownership shares by overlapping shareholders positively correlates with patent success beyond the shareholder overlap SOL itself. The coefficient estimate of 1.126 for SOL_HHI implies that an increase in the ownership concentration of shareholder overlap by one standard deviation (or 0.181) generates the same effect on patent success as raising SOL by 36.5% relative to its mean ($= [1.126 \times 0.181]\ /\ [3.247 \times 0.172]$). These estimates suggest that coordination problems among dispersed overlapping institutional investors represent an important impediment to the exercise of effective shareholder power. By contrast, concentration of shareholder overlap among only a few investors appears to facilitate holdup attenuation.

5.3 Litigation Risk

If shareholder overlap can indeed attenuate patent holdup, it should also attenuate patent conflicts mutating into costly patent litigation. Evidence for a negative relation between patent litigation risk and shareholder overlap is therefore evidence of the same governance channel operating through overlapping equity ownership. The previous literature (e.g., He and Huang, 2017; Newham et al., 2019; Gerakos and Xie, 2019) finds some evidence that investors internalize conflicts among firms in their equity portfolios. We extend this work to patent litigation based on patent litigation data from the LitAlert Database and Public Access to Court Electronic Records (PACER) for the sample period 1992–2007.

We construct a treatment sample of firms subject to patent infringement lawsuits. To be included in the sample, the defendant (i.e., the treatment firm) must cite the plaintiff (firm) in its patent filings at least once in the 10 years leading up to the patent litigation.[19] For each defendant in our sample, we find a control firm that also cites in its patent filings the same plaintiff firm during the same 10-year window. We require the control firm to share the same two-digit SIC code as the treated firm without ever being sued by the plaintiff (firm). To ensure that the control firm is similar to the treated firm, we measure their similarity based on the Mahalanobis-distance metric (Bloom et al., 2013) along six dimensions of firm characteristics, namely, log firm assets [$ln(Assets_{s,t-1})$], log market capitalization [$ln(MktCap_{s,t-1})$], Tobin's q ($TobinQ_{s,t-1}$), log R&D Stock [$ln(1 + R\&D\_Stock_{s,t-1})$], the number of patent filings over the past five years ($PatentStock_{s,t-1}$), and last year's stock return ($PastReturn_{s,t-1}$). Our choice of firm characteristics here follows Cohen, Gurun, and Kominers (2018).

Our final sample includes 972 firm observations, to which we fit a logit or a linear probability model

$$Litigation_{j,m,t} = \lambda_0 + \lambda_1 PSOL_{j,m,t-1} + \lambda_2 Controls_{j,m,t-1} + \epsilon_m + \eta_{j,m,t}, \tag{11}$$

where $Litigation_{j,m,t}$ is a litigation dummy with a value of 1 if firm j is a treatment firm (which is subject to patent litigation in year t), and zero otherwise. For each matched firm pair m, which combines a treated firm and a control firm, we include a firm pair fixed effect ϵ_m. In addition, lagged firm variables ($\text{Controls}_{j,m,t-1}$) seek to control for differences not captured by the matching procedure. The variable of interest is the *pairwise shareholder overlap* $PSOL_{j,m,t-1}$ of firm j with the common potential plaintiff firm. We estimate the model, either with or without controlling for firm characteristics.

Table 5, Panel A compares treated and control firms with respect to the six matching variables and the pairwise shareholder overlap ($PSOL$) with the plaintiff. The treated and control samples feature no systematic differences with respect to the six matching variables, but pairwise shareholder overlap with the plaintiff firm is unconditionally smaller by 0.013 (or 7% of the standard deviation of 0.18) for the treated firm sample subject to patent litigation from the plaintiff. Panel B reports the logit regression in Columns 1–2 and the linear probability model in Columns 3–4.

[19] For repeated plaintiff-defendant pairs, we include only the first litigation case in our sample to eliminate any endogenous equity holding change on the part of overlapping investors in response to a patent lawsuit.

All four specifications estimate the effect of (pairwise) shareholder overlap on the likelihood of litigation. For the linear probability model in Column 3, we can characterize the decrease in the likelihood of litigation as 19.8% [$= -1.101 \times 0.18$)] for an increase in the pairwise shareholder overlap by one standard deviation (or 0.18). We conclude that shareholder overlap with a potential upstream plaintiff predicts a reduction in patent litigation risk by an economically significant magnitude.

6 Causality and Endogeneity Issues

So far we have presented evidence consistent with the holdup attenuation hypothesis and its transmission logic without identifying a causal link between shareholder overlap and patent success. The next section presents evidence from a quasi-natural experiment followed by placebo tests and additional tests designed to discard various endogeneity concerns.

6.1 A Quasi-Natural Experiment

First, we report the effect of the quasi-natural experiment of financial institution mergers on both shareholder overlap and patent success. The literature (e.g., Holthausen, Leftwich, and Mayers, 1990; Keim and Madhavan, 1996; He and Huang, 2017) suggests that financial institutions often merge for reasons unrelated to the prospects of their portfolio holdings and that the acquiring firm typically keeps the target's portfolio holdings for an extended period of time without liquidating them because of transaction cost concerns. Therefore, if a downstream innovating firm and its upstream firm holding complementary patents are separately held by the two merging financial institutions before the merger, their shareholder overlap should increase right after the merger. Such merger events therefore create plausibly exogenous variation in shareholder overlap between two firms.

We form our merger sample following a similar methodology to that in He and Huang (2017). Specifically, we collect all merger deals between any two 13F financial institutions (with SIC Codes 6000–6999) announced during the period 1992–2006 from the SDC database. We require that a merger is completed within one year of its announcement and that the target stops its 13F filings within one year following the merger completion date. We use a 2.5% cut-off of institutional ownership as our definition of blockholding to increase our sample size, but using a 5% cut-off as in He and Huang (2017) yields qualitatively similar results. We identify as a treatment patent a downstream patent p that meets two criteria: First, the downstream firm owning patent p is blockheld by one of the merging institutions during the quarter immediately prior to the merger announcement. Second, the other merging institution does not blockhold the downstream firm but does blockhold at least one of patent p's upstream firms during the same quarter before the merger. Note that the choice of a relatively large ownership cut-off at 2.5% should predict a large increase in shareholder overlap for the treatment patents, and such an increase is likely to be persistent after the merger. Furthermore, our selection of treatment patents only uses portfolio holdings information prior to the merger, mitigating the concern that the actual post-event portfolio holdings may be endogenous.

For each treatment patent p, we define as control patents all patents q in the same patent class as p and filed in the same year by the same downstream firm owning patent p, but none of patent q's upstream firms are blockheld by the other merging institution. In total, we identify 43 merger deals featuring $13,151$ treated patents and $68,477$ control patents.

We employ a difference-in-difference approach to compare the success of treatment patents and control patents. For each merger deal, we consider a seven-year event window centered around the year of the merger event. We first verify that institution mergers do indeed lead to an increase in shareholder overlap for the treatment patents, and in the second step we examine the effect of such an exogenous increase in shareholder overlap on patent success. Specifically, we estimate the following two regressions:

$$\begin{aligned} sol_{j,e,t} &= \gamma_0 + \gamma_1 Treat_j + \gamma_2 Post\text{-}Merger_{j,e,t} + \qquad (12) \\ &\quad + \gamma_3 Treat_j \times Post\text{-}Merger_{j,e,t} + \eta_t + \xi_{e,s,f} + \varsigma_{j,e,t} \\ ln(1 + cites_{j,e,t}) &= \gamma_4 + \gamma_5 Treat_j + \gamma_6 Post\text{-}Merger_{j,e,t} + \qquad (13) \\ &\quad + \gamma_7 Treat_j \times Post\text{-}Merger_{j,e,t} + \theta_t + \omega_{e,s.f} + \nu_{j,e,t}, \end{aligned}$$

in which $sol_{j,e,t}$ and $ln(1+cites_{j,e,t})$ denote, respectively, the patent-level shareholder overlap and log forward citation count for patent j filed in year t, where patent j is either a treatment patent p or a control patent q associated with the merger event e. $Treat_j$ is a dummy of 1 if patent j is a treatment patent, and zero if otherwise. $Post\text{-}Merger_{j,e,t}$ is a time dummy of 1 if patent j's filing year t falls in the post-merger period for merger event e, and zero otherwise. We include calendar year fixed effects η_t and θ_t in the regression. Moreover, $\xi_{e,s,f}$ and $\omega_{e,s,f}$ denote fixed effects specific to any merger event e, the downstream firm s owning patent j, and the patent class f of patent j. Finally, $\varsigma_{j,t}$ and $\nu_{j,t}$ represent the error terms.

In Table 6, Columns 1 and 2 report the result for Eq. (12). The point estimate of 0.026 for the interaction term *Treat*×*Post-Merger* confirms that post-merger treated patents subject to financial institution mergers do indeed experience an economically significant increase in shareholder overlap (*sol*) at a magnitude of about 16.3% of its standard deviation. Column 2 measures the corresponding treatment effect on patent citations. The point estimate of 0.039 for the interacted term *Treat*×*Post-Merger* indicate that treated patents experience a 3.9% increase in patent citations after the merger—a difference that amounts to about 3% (2%) of the standard deviation (mean) of log patent citations [$ln(1+cites)$]. Both the increase in shareholder overlap and the increase in log patent citations are statistically significant at the conventional 5% level. Combining both results, we conclude that a one-standard-deviation increase in shareholder overlap (*sol*) generates patent citation growth of about 18% (12%) of its standard deviation (mean). Overall, the evidence from institution mergers points to an economically significant causal relationship between shareholder overlap and patent success.

The identifying assumption of the difference-in-difference approach is that, in the absence of treatment, the estimated difference-in-difference effect should be zero. We test this assumption using two different falsification tests. In the first, we replace the actual merger event year by a pseudo event year, which we arbitrarily set as the actual event year minus four years. In the second falsification test, we keep the actual merger event year, but replace one of the two merging financial institutions with a pseudo match not involved in any merger in a 10-year window centering around the merger event year.

We then carry out the same test procedure as before to examine whether the post-event treatment patents experience an increase in shareholder overlap with its upstream firms and an increase in future citations. Columns 3–4 and 5–6 in Table 6 report, respectively, the first and the second falsification test results. In both tests, post-event treatment patents do not feature any statistically significantly different level of shareholder overlap *sol* and patent success ($ln(1+cites)$) than control patents, suggesting that the identifying assumption holds in our setting.

6.2 Placebo Tests for Shareholder Overlap

To further probe the potential omitted variable bias, we propose two placebo tests. In these tests, we replace the *true* shareholder overlap (SOL) with a *placebo* shareholder overlap ($SOL\_Placebo1$ or $SOL\_Placebo2$). For $SOL\_Placebo1$, we replace each cited upstream firm with a *similar* firm that is *not cited* by the downstream firm in the given patent application year. A placebo firm is chosen based on the criteria that it must have the same four-digit SIC codes as the true upstream firm and have the shortest Euclidean distance to the true upstream firm in terms of (log) firm asset size and (log) number of patents filed in the past five years. $SOL\_Placebo2$ is constructed similarly but the placebo firms are matched to the true upstream firms based on their technological proximity (i.e., the closeness in the distribution of their patents across various technology fields) as defined by Bloom et al. (2013).

Table 7 reports the results. Column 1 reproduces the baseline SOL regression result (reported earlier in Table 2, Column 2). Columns 2–3 show that the two placebo measures of shareholder overlap do not feature any statistically significant correlation with patent success. If the positive SOL effect documented in the previous sections is driven by unobservable factors *unrelated to patent citation links*, such omitted variables should similarly lead to a positive relation between placebo shareholder overlap and patent success. Yet, we do not find such evidence for the two placebo measures of shareholder overlap, suggesting omitted variable bias cannot explain our results.

6.3 Shareholder Overlap around Patent Filing Years

Next, we examine whether reverse causality can explain the holdup attenuation effect of shareholder overlap. If investors in the upstream firms anticipate future revenue in the downstream firm associated with promising new patents, they may acquire shares in the downstream firm. In this case, a positive correlation between shareholder overlap and future patent success originates from an information advantage of the upstream firm owners with respect to the patent development in the downstream firm. Another channel for an endogenous adjustment of shareholder overlap is that investors might seek cross-firm investments in anticipation of the benefits from holdup attenuation of overlapping ownership. In this case, the cross-firm shareholder ownership structure adjusts so that it reduces holdup inefficiencies, and overlapping shareholders benefit from efficiency gains in the downstream firm.

To examine these two channels of reverse causality, we take each yearly cohort of patents filed between 1992 and 2007 and trace backward and forward (for up to three years) the shareholder overlap of all patent citation links. Specifically, for any particular patent p filed by firm s in year t, we fix its cited upstream firms $s\prime$ and calculate the average shareholder overlap between firm s and its upstream firms $s\prime$ at the end of year $t+k$ (with $k=-3,-2,\ldots,2,3$), denoted by $sol_p(t,s,k)$.[20] We then aggregate it to the firm level as $SOL(t,s,k)=\frac{1}{N_p}\sum_{p=1}^{N_p} sol_p(t,s,k)$ over all N_p patents filed by firm s in year t. In the second aggregation (over all N_s patent-filing firms), we calculate the average shareholder overlap at lag k for patents filed in year t as $\overline{SOL}(t,k)=\frac{1}{N_s}\sum_{s=1}^{N_s} SOL(t,s,k)$. For example, $\overline{SOL}(t,-3)$ denotes the average shareholder overlap between a downstream firm and its upstream firms, measured based on ownership at the end of year $t-3$ for the patent cohort filed in year t. Figure 2 plots the evolution of the average shareholder overlap $\overline{SOL}(t,k)$ for the different patent cohorts.

Overall, we find no evidence that the average shareholder overlap reacts endogenously in anticipation of patent rents from future patent filing. This finding may not be surprising for at least two reasons. First, patent developments are generally kept secret so that public information is extremely scarce. Second, legal restrictions on insider trading limit the scope for stock trading on private information.

6.4 Shareholder Influence Based on Information

Some investors may specialize in acquiring stakes in innovative firms that have a disproportionate share of patents. These technology-savvy shareholders may bring particular knowledge to the innovation process, allowing for better governance of the innovating firm. Such a *shareholder innovation focus* is directly measurable based on ownership data in a simple three-step procedure. In the first step, we define for each listed firm s'' the *firm innovation focus* (FIF) as the ratio of the future citation count of all patents filed by firm s'' in year t to the industry average citation count during the same period. In the second step, we account for all institutional investors i in firm s and calculate their respective *investor innovation focus* (IIF) as the value-weighted average

[20] We note that the full set of $sol_p(t,s,k)$ cannot be calculated for all years. For example, for patents filed in 1992, we can only calculate $sol_p(t,s,k)$ for $k>=-1$.

firm innovation focus for all stocks s'' in their respective investment portfolios except for stock s itself. In the third step, the *shareholder innovation focus* (SIF) for firm s is defined as the value-weighted average of investor innovation focus for all shareholders i in firm s,

$$SIF_{s,t} = \sum_i w_{i,s,t} IIF_{i,s,t} \quad , \tag{14}$$

where $w_{i,s,t}$ represents the equity shares held by institutional investor i relative to the aggregate holdings of all institutional investors in firm s at the end of year t. A firm mostly owned by investors with a high IIF should feature a high SIF value. Shareholders' governance competence (proxied by $SIF_{s,t}$) with respect to the innovating firm s should have a positive effect on the patent success of the firm.

Table 8, Panel A, Column 2 includes shareholder innovation focus $SIF_{s,t-1}$ as an additional explanatory variable for patent success, controlling for the general institutional ownership level $IO_{s,t-1}$ in a firm. As expected, we find that the general innovation focus of a firm's shareholders fosters patent success of the respective firm, but the SOL effect remains strong even after accounting for this factor.

7 Robustness Issues

We conduct a number of additional robustness checks in this section.

First, Bloom, et al. (2013) show two countervailing *R&D spillover* effects on a firm's innovation success: A positive effect due to technology spillover (from other firms that operate in similar technology fields) and a negative effect due to product market rivalry (from other firms that operate in similar product markets). Table 8, Panel A, Column 3 shows that even after accounting for these two factors, measured by $ln(SpillTech)$ and $ln(SpillSIC)$, the shareholder overlap effect remains quantitatively unchanged.

Second, we split our sample firms into two subsamples based on their average yearly citation count. Table 8, Panel A, Columns 4 and 5 report, respectively, the results for the 50% of firms with the highest average citations and the remaining 50% of firms. It's reassuring that the SOL effect is statistically and economically significant in both subsamples.

Third, as patent citation count is often perceived as a value signal, overlapping institutional shareholders may promote cross-citations among firms in which they also have a joint equity stake. To eliminate such spurious effects from our regression, we exclude all citations that come from the upstream firms cited in the patent filings of the downstream firm. Table 8, Panel A, Column 6 repeats the baseline regression but uses this modified patent citation $ln(1 + CITES^F)$ as the dependent variable. The estimate for SOL is quantitatively similar to that of the baseline regression, suggesting that any potential bias arising from such citation manipulation is small.

Fourth, we estimate an alternative regression specification using a negative binominal model with $CITES_{s,t}$ as the dependent variable. Table 8, Panel A, Column 7 shows that the SOL effect remains strong in this specification.

Fifth, in unreported results, we replace our baseline measure of shareholder overlap $SOL_{s,t-1}$, which is based on ownership stake at the end of year $t-1$, with $SOL_{s,t-2}$ or $SOL_{s,t-3}$, which is measured based on ownership stake at the end of year $t-2$ or $t-3$. The SOL estimate remains highly statistically and economically significant, albeit at a smaller magnitude.

Sixth, our baseline measure of $CITES$ follows Hall et al. (2001) in adjusting citation count based on the shape of the citation-lag distribution. We reproduce our results using an alternative aggregation proposed by Lerner et al. (2011), in which we count only the citations received during the calendar year of the patent grant and the three subsequent years. This alternative citation count is denoted by $CITES^{3yr}$. The results, reported in Table 8, Panel B, are robust to this alternative measure of citation count.

Seventh, we use the dollar value of patents estimated by Kogan et al. (2017) as an alternative measure of patent success. Table 8, Panel C reports the results. The point estimate of 4.135 in Column 1 implies that a one-standard-deviation increase in SOL increases a firm's log average estimated patent value by about 17% (19%) of its standard deviation (mean). The estimated effect is quantitatively similar to that reported in Table 2 with patent success proxied by forward citations.[21] The citation measure has the advantage that it is directly observable for a large number of firms with a long history. In contrast, the precision of the dollar values of patents estimated by Kogan et al. (2017) relies on the validity of the model assumptions they use to derive the estimates. Any violation of the assumptions can cause the estimates to deviate away from their true values.

Eighth, we measure the novelty of a firm's patent projects using five different indicators. The

[21] We follow the same methodology used in Table 2 to construct the pre-sample mean for patent values. Again, using an alternative cutoff of 20, 15, or 10 years does not change our results qualitatively.

first two indicators, originality and generality, follow from Trajtenberg, Henderson, and Jaffe (1997). A patent that cites a greater spectrum of technology classes has a higher originality score, and a patent that is cited by patents from a greater spectrum of technology classes has a higher generality score. The third indicator, innovative search quality, follows from Manso, Balsmeier, and Fleming (2019). A firm that focuses more on exploratory research, as opposed to exploitative research, has a higher innovative search score. The fourth indicator counts the number of top 10% most-cited patents a firm has filed each year, and the last indicator counts the number of patent filings each year that belong to the patent classes in which a firm has never filed patents before. Table 8, Panel D shows that shareholder overlap positively relates to downstream firms pursuing more novel research ideas.

8 Conclusion

This paper provides a property rights perspective on the success of corporate innovation processes. The commercial success of a patent often depends on access to complementary patents not under the direct control of its innovator. From a property rights perspective, the "extended boundary" of a downstream innovating firm includes such complementary patents if the downstream innovator and its upstream firm that owns those complementary patents are linked together by common shareholders holding a joint equity stake in both firms.

We use citation links in patent filings to measure patent complementarity and show that such links feature a high correlation with probability of patent litigation, number of licensing agreements, and amount of royalty transfer between firms. *Shareholder overlap* (SOL) is defined as the aggregate minimum ownership share that investors own jointly in the downstream innovating firm and the upstream firms controlling the complementary assets. A downstream innovating firm with a large SOL value can be interpreted as having an extended firm boundary.

Our main analysis concerns the role of *shareholder overlap* for patent success: It correlates positively with both the intensive and extensive margins of patent production in an economically significant manner. This finding is robust to a variety of control variables and the inclusion of time, industry, and firm fixed effects. We use merger events of financial institutions as a quasi-natural experiment for exogenous variation in patent-level shareholder overlap sol. Such merger events significantly increase sol, and patents with a resulted "extended boundary" of ultimate asset ownership receive substantially more future citations than a group of otherwise similar control patents. We also apply two placebo tests to show that the citation link to the upstream patent is crucial for the holdup attenuation effect of shareholder overlap and that the relationship between patent success and shareholder overlap does not appear to be driven by reverse causality.

We highlight two further dimensions of ownership structure. First, shareholder overlap coming from more dedicated investors tends to contribute more to the holdup attenuation—suggesting that the "extended boundary" of the innovating firm also depends on the types of institutional shareholders. Second, the ownership concentration of shareholder overlap matters independently of the overlap level. This could be explained by the existence of coordination and free-rider problems among a large and dispersed group of overlapping shareholders. Finally, shareholder overlap significantly reduces the patent litigation risk of a downstream innovating firm.

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Table 1: Summary Statistics

Reported are the summary statistics of the regression variables. The key firm-level dependent variables are (i) $CITES_{s,t}$, the number of future citations received by the cohort of patents filed by firm s in year t; (ii) $N_{s,t}$, the number of patents filed by firm s in year t; (iii) $\overline{cites}_{s,t}$, the average future citation count per patent for the cohort of patents filed by firm s in year t; (iv) $R\&D\ Exp_{s,t}/Asset_{s,t-1}$, the R&D expenditure to the total assets ratio, (v) $CITES^F_{s,t}$, a filtered citation measure, which removes all citations coming from upstream firms that firm s has cited in its patent filings in year t. Other dependent variables include a three-year citation measure ($CITES\_3yr_{s,t}$), a filtered three-year citation measure ($CITES\_3yr^F_{s,t}$), log of a patent's dollar value [$ln(Patent\ Dollar\ Value_{s,t})$], patent originality ($Originality_{s,t}$), patent generality ($Generality_{s,t}$), log number of patents belonging to the top 10% most cited patents in their respective patent class [$ln(1+N^{Top10\%}_{s,t})$], log number of patents belonging to a new patent class in which a firm has never filed patents before [$ln(1+N^{NewClass}_{s,t})$], and innovative search index ($Innov.\ Search_{s,t}$) as a measure for explorative innovation activities. At the patent level, we denote by $sol_{p,t}$ and $cites_{p,t}$, respectively, the patent-level shareholder overlap and the total number of future citations received by patent p, filed in year t. $SOL_{s,t-1}$ refers to the shareholder overlap for firm s in year $t-1$. We decompose $SOL_{s,t-1}$ into the shareholder overlap originating from dedicated investors ($SOL\_Ded_{s,t-1}$) and that from non-dedicated investors ($SOL\_NonDed_{s,t-1}$). $SOL\_Placebo1_{s,t-1}$ and $SOL\_Placebo2_{s,t-1}$ are the two placebo measures of shareholder overlap. $IO_{s,t-1}$, $IO^{SOL}_{s,t-1}$, and $IO^{NOL}_{s,t-1}$ represent the institutional ownership of, respectively, all shareholders, overlapping shareholders, and non-overlapping shareholders in firm s at the end of year $t-1$. $SIF_{s,t-1}$ and $SOL\_HHI_{s,t-1}$ are, respectively, the shareholder innovation focus and the average Herfindahl-Hirschman Index of shareholder overlap for firm s at the end of year $t-1$. $ln(SpillTECH_{s,t-1})$ and $ln(SpillSIC_{s,t-1})$ measures, respectively, the extent of technology spillover and product market rivalry effect of $R\&D$ for firm s in year $t-1$. The control variables include log total assets [$ln(Assets_{s,t-1})$], log cumulative R&D investment [$ln(1+R\&D\_Stock_{s,t-1})$], log capital to labor ratio [$ln(K/L_{s,t-1})$], leverage ($Leverage_{s,t-1}$), and the average proportion of privately owned upstream patents ($Private\ Patent\ Share_{s,t-1}$). Detailed definitions of the variables are given in Appendix A.

	Obs.	Mean	Median	S.D.	Skewness	Min.	P25	P75	Max.
Dependent Variables (measured in year t)									
$ln(1+CITES)$	18,763	3.948	3.912	2.071	0.114	0.000	2.584	5.305	11.640
$ln(1+\overline{cites})$	18,763	2.385	2.455	1.145	−0.172	0.000	1.702	3.127	6.643
$ln(1+N)$	18,763	1.966	1.609	1.342	1.354	0.693	0.693	2.639	8.395
$R\&D\ Exp/Assets$	18,763	0.123	0.061	0.213	8.353	0.000	0.014	0.151	7.478
$ln(1+CITES^F)$	18,763	3.904	3.870	2.054	0.118	0.000	2.549	5.249	11.565
$ln(1+CITES\_3yr)$	18,763	2.671	2.485	1.924	0.541	0.000	1.099	3.932	10.701
$ln(1+CITES\_3yr^F)$	18,763	2.608	2.485	1.896	0.553	0.000	1.099	3.850	10.606
$ln(Patent\ Dollar\ Value)$	18,763	2.481	2.087	2.731	0.589	−4.533	0.174	4.241	11.746
$Originality$	18,763	0.474	0.488	0.195	−0.471	0.000	0.367	0.609	0.933
$Generality$	18,763	0.338	0.352	0.243	0.084	0.000	0.113	0.524	0.902
$ln(1+N^{Top10\%})$	18,763	0.645	0.000	0.955	1.850	0.000	0.000	1.099	6.061
$ln(1+N^{NewClass})$	18,763	0.571	0.693	0.647	1.019	0.000	0.000	1.099	4.220
$Innov.\ Search$	18,763	0.191	0.086	0.237	1.266	0.000	0.000	0.314	0.996
$ln(1+cites)$	81,628	2.079	2.132	1.313	0.055	0.000	1.176	2.985	6.830
sol	81,628	0.269	0.264	0.160	0.375	0.000	0.132	0.379	0.847
Independent Variables (measured in year $t-1$)									
SOL	18,763	0.172	0.164	0.120	0.446	0.000	0.077	0.254	0.727
SOL_Ded	18,763	0.003	0.001	0.007	5.136	0.000	0.000	0.003	0.173
SOL_NonDed	18,763	0.160	0.153	0.111	0.428	0.000	0.072	0.236	0.698
$SOL\_Placebo1$	18,763	0.158	0.158	0.083	0.375	0.000	0.097	0.211	0.580
$SOL\_Placebo2$	18,763	0.130	0.131	0.071	0.553	0.000	0.081	0.173	0.780
SIF	18,763	0.249	0.241	0.073	2.645	0.000	0.206	0.282	2.699
SOL_HHI	18,763	0.186	0.125	0.181	1.986	0.000	0.077	0.239	1.000
IO	18,763	0.482	0.499	0.267	−0.052	0.000	0.254	0.695	1.000
IO^{SOL}	18,763	0.378	0.364	0.278	0.189	0.000	0.116	0.614	1.000
IO^{NOL}	18,763	0.100	0.037	0.158	2.668	−0.000	0.004	0.123	1.119
$ln(SpillTECH)$	18,763	10.615	10.748	1.059	−1.027	1.887	10.055	11.337	12.747
$ln(SpillSIC)$	18,608	8.626	9.035	2.301	−1.147	−8.179	7.502	10.232	12.607

Table 1 continued

	Obs.	Mean	Median	S.D.	Skewness	Min.	P25	P75	Max.
Controls (measured in year $t-1$)									
$ln(Assets)$	18,763	5.785	5.585	2.219	0.403	0.209	4.141	7.276	14.194
$ln(1 + R\&D\_Stock)$	18,763	3.746	3.881	2.235	0.062	0.000	2.385	5.112	10.714
$ln(K/L)$	18,763	3.663	3.558	0.991	0.523	−2.492	3.045	4.207	9.957
Leverage	18,763	0.140	0.081	0.165	1.463	0.000	0.001	0.233	0.786
Private Patent Share	18,763	0.736	0.766	0.193	−0.859	0.000	0.616	0.879	1.000

Table 2: Baseline Regressions

Reported are the firm-level OLS regressions of patent success that are respectively measured by i) $ln(1+CITES_{s,t})$, log number of future citations received by the cohort of patents filed by firm s in year t; ii) $ln(1+\overline{cites})$, log average future citation count per patent for the cohort of patents filed by firm s in year t; and iii) $ln(1+N_{s,t})$, log number of successful patent applications filed by firm s in year t. The sample period is 1992–2007. The key variable of interest $SOL_{s,t-1}$ measures the lagged average shareholder ownership overlap at the end of year $t-1$ between the innovating firm s and its upstream firms owning complementary patents. The control variables include log total assets [$ln(Assets_{s,t-1})$], log cumulative R&D investment [$ln(1+R\&D\_Stock_{s,t-1})$], log capital to labor ratio [$ln(K/L_{s,t-1})$], leverage ($Leverage_{s,t-1}$), and the average proportion of privately owned upstream patents ($Private\ Patent\ Share_{s,t-1}$) for firm s in year $t-1$. All regressions control for a full set of year dummies and industry dummies based on four-digit SIC codes. Firm fixed effects are based on Blundell et al. (1999). Robust standard errors clustered at the firm level are reported in parentheses. Also reported are the total number of observations and the adjusted R-squared. ***, **, and * denote the 1%, 5%, and 10% significance level, respectively.

Dependent Variables:	$ln(1+CITES)$		$ln(1+\overline{cites})$		$ln(1+N)$	
	(1)	(2)	(3)	(4)	(5)	(6)
SOL	3.570***	3.234***	1.192***	1.132***	1.939***	1.733***
	(0.210)	(0.206)	(0.116)	(0.116)	(0.130)	(0.126)
Controls:						
$ln(Assets)$	0.100***	0.054**	−0.044***	−0.050***	0.132***	0.087***
	(0.022)	(0.021)	(0.011)	(0.012)	(0.015)	(0.014)
$ln(1+R\&D\_Stock)$	0.425***	0.355***	0.026**	0.020*	0.360***	0.274***
	(0.022)	(0.022)	(0.010)	(0.011)	(0.018)	(0.016)
$ln(K/L)$	0.059**	0.076***	0.018	0.019	0.033*	0.063***
	(0.029)	(0.028)	(0.016)	(0.016)	(0.019)	(0.018)
$Leverage$	−0.425***	−0.369***	−0.108	−0.102	−0.296***	−0.217***
	(0.128)	(0.127)	(0.066)	(0.066)	(0.080)	(0.079)
$Private\ Patent\ Share$	0.108	0.011	0.068	0.056	0.033	−0.072
	(0.105)	(0.103)	(0.060)	(0.060)	(0.061)	(0.059)
Year & Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE (BGV)	No	Yes	No	Yes	No	Yes
Observations	18,763	18,763	18,763	18,763	18,763	18,763
Adj. R^2	0.532	0.545	0.427	0.428	0.629	0.657

Table 3: R&D Expenditure and Shareholder Overlap

Reported are OLS regressions of the R&D expenditure (relative to assets) for the sample period 1992–2007. $R\&D\ Exp_{s,t}/Assets_{s,t-1}$ denotes the R&D expenditure to the total firm assets ratio for firm s in year t. $SOL_{s,t-1}$ measures the average shareholder ownership overlap at the end of year $t-1$ between the innovating firm s and its upstream firms owning complementary patents. $IO_{s,t-1}$, $IO^{SOL}_{s,t-1}$, and $IO^{NOL}_{s,t-1}$ represent the institutional ownership of, respectively, all shareholders, overlapping shareholders, and non-overlapping shareholders in firm s at the end of year $t-1$. The control variables include log total assets [$ln(Assets_{s,t-1})$], log capital to labor ratio [$ln(K/L_{s,t-1})$], leverage ($Leverage_{s,t-1}$), and the average proportion of privately owned upstream patents ($Private\ Patent\ Share_{s,t-1}$) for firm s in year $t-1$. All regressions control for a full set of year dummies and firm dummies. Robust standard errors clustered at the firm level are reported in parentheses. Also reported are the total number of observations and the adjusted R-squared. ***, **, and * denote the 1%, 5%, and 10% significance level, respectively.

Dependent Variable:	*R&D Exp/Assets*		
	(1)	(2)	(3)
SOL	0.117***	0.115***	
	(0.022)	(0.022)	
IO		0.016	
		(0.016)	
IO^{SOL}			0.035**
			(0.015)
IO^{NOL}			0.008
			(0.014)
Controls:			
$ln(Assets)$	−0.104***	−0.105***	−0.103***
	(0.009)	(0.009)	(0.008)
$ln(K/L)$	0.007	0.008	0.007
	(0.006)	(0.006)	(0.006)
$Leverage$	0.006	0.006	0.005
	(0.018)	(0.018)	(0.018)
$Private\ Patent\ Share$	−0.007	−0.007	−0.015
	(0.015)	(0.015)	(0.016)
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Observations	18,763	18,763	18,763
Adj. R^2	0.565	0.565	0.564

Table 4: SOL Heterogeneity

Column 1 reproduces the baseline regression reported in Table 2, Column 2. In Column 2, we decompose shareholder overlap ($SOL_{s,t-1}$) into the part originating from dedicated investors ($SOL\_Ded_{s,t-1}$) and the part from non-dedicated investors ($SOL\_NonDed_{s,t-1}$). At the end of each year, we sort all institutional investors by their portfolio concentration (in descending order) and churn ratio (in ascending order). We label investors in the top 50% of both the portfolio concentration sort and the churn ratio sort (i.e., high concentration and low turnover) as dedicated investors and the remaining investors as non-dedicated investors. Column 3 expands the baseline regression by including the average Herfindahl-Hirschman Index of the ownership concentration of overlapping shareholders, $SOL\_HHI_{s,t-1}$. The control variables include log total assets ($ln(Assets_{s,t-1})$), log cumulative R&D investment [$ln(1 + R\&D\_Stock_{s,t-1})$], log capital to labor ratio [$ln(K/L_{s,t-1})$], leverage ($Leverage_{s,t-1}$), and the average proportion of privately owned upstream patents ($Private\ Patent\ Share_{s,t-1}$) for firm s in year $t-1$. The sample period is 1992–2007. We report in the last row the p-value for the null hypothesis of equal coefficients in Column 2. All regressions control for a full set of year dummies and industry dummies based on four-digit SIC codes. Firm fixed effects are based on Blundell et al. (1999). Robust standard errors clustered at the firm level are reported in parentheses. Also reported are the total number of observations and the adjusted R-squared. ***, **, and * denote the 1%, 5%, and 10% significance level, respectively.

Dependent Variable:	$ln(1 + CITES)$		
	(1)	(2)	(3)
SOL	3.234***		3.247***
	(0.206)		(0.204)
SOL_Ded		9.768***	
		(2.730)	
SOL_NonDed		3.256***	
		(0.220)	
SOL_HHI			1.126***
			(0.087)
Controls:			
$ln(Assets)$	0.054**	0.053**	0.106***
	(0.021)	(0.021)	(0.022)
$ln(1 + R\&D\_Stock)$	0.355***	0.354***	0.359***
	(0.022)	(0.022)	(0.022)
$ln(K/L)$	0.076***	0.076***	0.078***
	(0.028)	(0.028)	(0.028)
$Leverage$	−0.369***	−0.353***	−0.423***
	(0.127)	(0.127)	(0.126)
$Private\ Patent\ Share$	0.011	0.003	0.217**
	(0.103)	(0.103)	(0.105)
Year and Industry FE	Yes	Yes	Yes
Firm FE (BGV)	Yes	Yes	Yes
Observations	18,763	18,763	18,763
Adj. R^2	0.545	0.545	0.551
$H_0 : SOL\_Ded = SOL\_NonDed$		0.03	

Table 5: Litigation and Shareholder Overlap

We report logit and linear probability regressions for the likelihood of being accused of patent infringement in a lawsuit. We construct a treatment sample of firms subject to patent infringement lawsuits. To be included in the sample, the defendant (i.e., the treatment firm) must cite the plaintiff (firm) in its patent filings at least once in the 10 years leading up to the patent litigation. For each defendant in our sample, we find a control firm that also cites in its patent filings the same plaintiff firm during the same 10-year window. We require the control firm to share the same two-digit SIC code as the treated firm without ever being sued by the plaintiff (firm). To ensure that the control firm is similar to the treated firm, we measure their similarity based on the Mahalanobis-distance metric along six dimensions of firm characteristics, namely, log firm assets [$ln(Assets_{s,t-1})$], log market capitalization [$ln(MktCap_{s,t-1})$], Tobin's q ($TobinQ_{s,t-1}$), log R&D Stock [$ln(1 + R\&D\_Stock_{s,t-1})$], the number of patents filed over the past five years ($PatentStock_{s,t-1}$), and last year's stock return ($PastReturn_{s,t-1}$). Panel A reports the balance tests on the six matching firm characteristics and pairwise shareholder overlap ($PSOL_{s,t-1}$). Panel B reports the estimates for the Logit model in Columns 1–2 and the linear probability model in Columns 3–4. We also report the marginal effect on litigation probability of a one-standard-deviation increase in pairwise shareholder overlap $POSL$, with all covariates evaluated at their mean values. All four regressions include firm pair dummies, which identify each matched firm pair. Robust standard errors clustered at the firm level are reported in parentheses. Also reported are the total number of observations and pseudo R-squared. ***, **, and * denote the 1%, 5%, and 10% significance level, respectively.

Panel A: Balance Tests

		Treated		Control		Difference	
	Obs.	Mean	S.D.	Mean	S.D.	(2)-(4)	S.E.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$PSOL$	486	0.239	0.178	0.252	0.182	−0.013***	0.005
$ln(Assets)$	486	7.934	2.018	7.944	1.944	0.010	0.039
$ln(MktCap)$	486	15.302	2.073	15.302	1.958	−0.001	0.041
$TobinQ$	486	0.348	0.221	0.344	0.205	0.004	0.006
$ln(1 + R\&D\_Stock)$	486	6.527	2.000	6.581	1.971	−0.054	0.038
$Patent\ Stock$	486	5.239	1.880	5.305	1.860	−0.066	0.040
$Past\ Return$	486	0.191	0.546	0.180	0.500	0.012	0.015

Panel B: Regression Results

Dependent Variable:	$Litigation(0/1)$			
	Logit		Linear Prob.	
	(1)	(2)	(3)	(4)
$PSOL$	−4.548***	−5.257***	−1.101**	−1.244**
	(1.648)	(1.769)	(0.529)	(0.550)
$ln(Assets)$		0.373		0.090
		(0.563)		(0.195)
$ln(MktCap)$		0.657		0.158
		(0.437)		(0.149)
$TobinQ$		2.131		0.518
		(1.960)		(0.672)
$ln(1 + R\&D\_Stock)$		−0.613		−0.147
		(0.464)		(0.159)
$Patent\ Stock$		−0.447		−0.109
		(0.354)		(0.122)
$Past\ Return$		0.538		0.131
		(0.569)		(0.195)
Pair fixed effects	Yes	Yes	Yes	Yes
Marginal effect at means	−0.205	−0.237	−0.198	−0.224
Observations	972	972	972	972
Pseudo R^2 or R^2	0.010	0.025	0.014	0.033

Table 6: A Quasi-Natural Experiment of Shareholder Overlap Change

In this table, we use a quasi-natural experiment where patent-level shareholder overlap increases exogenously for treatment patents due to a merger of financial institutions. We then employ a difference-in-difference approach to compare the success of treatment patents (*Treat* = 1) and control patents (*Treat* = 0). The dummy variable *Post-Merger* marks as 1 all patents filed after the merger event, and zero otherwise. Columns 1–2 report the result for the quasi-natural experiment and Columns 3–6 the results of two falsification tests. The dependent variables in Columns 1 and 2 are, respectively, the patent-level shareholder overlap ($sol_{j,e,t}$) and the log future citation count [$ln(1 + cites_{j,e,t})$] for patent j filed in year t and associated with a merger event e. For each merger deal, we consider a seven-year event window centered around the year of the merger event. In falsification test A, we pick a pseudo event year for each financial institution merger, which is four years before the actual date of the merger. In falsification test B, we keep the actual merger year unchanged, but replace either the target or the acquirer firm with a pseudo merger partner not involved in any merger in a 10-year window centering around the merger event year. All regressions control for interacted merger event-firm-patent class fixed effects and calendar year fixed effects. Robust standard errors are reported in parentheses, which are clustered at the merger event level. Also reported are the total number of observations and the adjusted R-squared. ***, **, and * denote the 1%, 5%, and 10% significance level, respectively.

	Natural Experiment		Falsification Test A		Falsification Test B	
Dependent Variables:	sol	$ln(1 + cites)$	sol	$ln(1 + cites)$	sol	$ln(1 + cites)$
	(1)	(2)	(3)	(4)	(5)	(6)
Treat × *Post-Merger*	0.026***	0.039**	0.003	0.025	0.009	−0.007
	(0.005)	(0.016)	(0.008)	(0.020)	(0.007)	(0.015)
Treat	0.126***	0.046***	0.101***	0.044**	0.088***	0.069***
	(0.010)	(0.016)	(0.012)	(0.019)	(0.010)	(0.010)
Post-Merger	−0.005	−0.005	0.002	−0.012	−0.004	−0.003
	(0.004)	(0.012)	(0.005)	(0.017)	(0.003)	(0.006)
Event × Firm × Tech. FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	81,628	81,628	56,173	56,173	198,073	198,073
Adj. R^2	0.322	0.125	0.300	0.152	0.331	0.130

Table 7: Placebo Tests with Respect to Shareholder Overlap

This table reports two placebo tests for the baseline regression reported in Table 2, which we reproduce in Column 1 of this table. In the tests, we replace the true shareholder overlap (SOL) with a placebo shareholder overlap ($SOL\_Placebo1$ or $SOL\_Placebo2$). For $SOL\_Placebo1$, we replace each cited upstream firm with a similar firm that is not cited by the downstream firm in the given patent application year. A placebo firm is chosen based on the criteria that it must have the same four-digit SIC codes as the true upstream firm and have the shortest Euclidean distance to the true upstream firm in terms of (log) firm asset size and (log) number of patents filed in the past five years. $SOL\_Placebo2$ is constructed similarly but the placebo firms are matched to the true upstream firms based on their technological proximity. The control variables include log total assets $[ln(Assets_{s,t-1})]$, log cumulative R&D investment $[ln(1 + R\&D\_Stock_{s,t-1})]$, log capital to labor ratio $[ln(K/L_{s,t-1})]$, leverage ($Leverage_{s,t-1}$), and the average proportion of privately owned upstream patents ($Private\ Patent\ Share_{s,t-1}$) for firm s in year $t-1$. The sample period is 1992–2007. All regressions control for a full set of year dummies and industry dummies based on four-digit SIC codes. Firm fixed effects are based on Blundell et al. (1999). Robust standard errors clustered at the firm level are reported in parentheses. Also reported are the total number of observations and the adjusted R-squared. ***, **, and * denote the 1%, 5%, and 10% significance level, respectively.

Dependent Variable:	$ln(1 + CITES)$		
	(1)	(2)	(3)
SOL	3.234^{***}		
	(0.206)		
$SOL\_Placebo1$		-0.069	
		(0.248)	
$SOL\_Placebo2$			-0.300
			(0.230)
Firm Controls	Yes	Yes	Yes
Year and Industry FE	Yes	Yes	Yes
Firm FE (BGV)	Yes	Yes	Yes
Observations	18,763	18,763	18,763
Adj. R^2	0.545	0.532	0.532

Table 8: Robustness

This table reports regression results on various robustness tests. Panel A reports robustness tests on model specifications. Additional explanatory variables, including institutional ownership ($IO_{s,t-1}$), shareholder innovation focus ($SIF_{s,t-1}$), technology spillover ($ln(SpillTech_{s,t-1})$), and the product market rivalry effect of R&D ($ln(SpillSIC_{s,t-1})$) are added to Columns 2–3. Columns 4-5 report, respectively, the results for the 50% of firms with the highest average yearly citations (H. CITES) and the remaining 50% of firms (L. CITES).The dependent variable in Columns 1–5 is $ln(1 + CITES_{s,t})$. Column 6 uses a filtered citation measure, $ln(1 + CITES^F_{s,t})$, as the dependent variable, which removes all citations coming from those upstream firms that firm s has cited in its patent filings in year t. Column 7 reports the estimation result using a negative binominal model. Panel B uses alternative count statistics $CITES\_3yr_{s,t}$ and $CITES\_3yr^F_{s,t}$ as dependent variables, which count only citations received during the patent grant year and three subsequent years for patents filed by firm s in year t. Panel C measures patent success by the estimated log dollar value of a patent, $ln(Patent\ Dollar\ Value_{s,t})$. Columns 4–5 report, respectively, the results for the top 50% of firms with the highest average yearly estimated patent value (High Value) and the remaining 50% of firms (Low Value). Panel D reports regression results on five measures of patent novelty: $Originality_{s,t}$, $Generality_{s,t}$, $Innov.\ Search_{s,t}$, $ln(1 + N^{Top10\%}_{s,t})$, and $ln(1 + N^{NewClass}_{s,t})$. All regressions control for the same set of control variables and fixed effects as those included in Table 2, Column 2. Robust standard errors clustered at the firm level are reported in parentheses. Also reported are the total number of observations and the adjusted R-squared. ***, **, and * denote the 1%, 5%, and 10% significance level, respectively. Detailed variable definitions are provided in Appendix A.

Panel A: Robustness on model specifications

Dependent Variables:	$ln(1 + CITES)$					$ln(1 + CITES^F)$	Neg. Binomial $CITES$
				H. CITES	L. CITES		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
SOL	3.234***	3.192***	3.218***	2.511***	2.293***	3.190***	2.831***
	(0.206)	(0.205)	(0.209)	(0.366)	(0.187)	(0.208)	(0.279)
IO		−0.295***	−0.298***	−0.699***	0.088	−0.296***	−0.470***
		(0.092)	(0.092)	(0.128)	(0.086)	(0.092)	(0.086)
SIF		0.855***	0.926***	1.277**	0.070	0.932***	0.634
		(0.307)	(0.310)	(0.571)	(0.257)	(0.309)	(0.415)
$ln(SpillTECH)$			0.101***	−0.065	0.126***	0.103***	0.107***
			(0.032)	(0.054)	(0.026)	(0.032)	(0.034)
$ln(SpillSIC)$			−0.039**	−0.039	−0.011	−0.040**	−0.018
			(0.018)	(0.032)	(0.016)	(0.018)	(0.020)
Controls and FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,763	18,763	18,608	9,465	9,143	18,608	18,608
Adj. R^2	0.545	0.546	0.547	0.515	0.257	0.543	

Panel B: Measuring patent success with three years' citations

Dependent Variables:	$ln(1 + CITES\_3yr)$					$ln(1 + CITES\_3yr^F)$	Neg. Binomial $CITES\_3yr$
				H. CITES	L. CITES		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
SOL	2.135***	2.137***	2.144***	1.574***	1.501***	2.076***	2.572***
	(0.171)	(0.170)	(0.173)	(0.319)	(0.134)	(0.171)	(0.261)
IO		−0.268***	−0.269***	−0.664***	−0.060	−0.264***	−0.413***
		(0.079)	(0.079)	(0.116)	(0.062)	(0.078)	(0.085)
SIF		0.441**	0.482**	0.721	0.075	0.469**	1.206***
		(0.215)	(0.215)	(0.482)	(0.164)	(0.212)	(0.373)
$ln(SpillTECH)$			0.116***	0.021	0.105***	0.120***	0.127***
			(0.027)	(0.048)	(0.019)	(0.025)	(0.032)
$ln(SpillSIC)$			−0.031**	−0.048*	−0.016	−0.031**	−0.026
			(0.015)	(0.026)	(0.012)	(0.015)	(0.019)
Controls and FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,763	18,763	18,608	9,411	9,197	18,608	18,608
Adj. R^2	0.614	0.615	0.617	0.620	0.342	0.613	

Table 8 Continued

Panel C: Measuring patent success with the estimated patent value

Dependent Variables:	$ln(Patent\ Dollar\ Value)$				
				High Value	Low Value
	(1)	(2)	(3)	(4)	(5)
SOL	4.135***	3.827***	3.860***	3.421***	1.976***
	(0.227)	(0.227)	(0.230)	(0.318)	(0.200)
IO		0.267**	0.272**	−0.315*	0.409***
		(0.106)	(0.107)	(0.163)	(0.086)
SIF		2.199***	2.220***	1.939***	0.988***
		(0.390)	(0.386)	(0.694)	(0.306)
$ln(SpillTECH)$			0.184***	0.153**	0.103***
			(0.031)	(0.070)	(0.027)
$ln(SpillSIC)$			−0.042**	−0.107***	0.020
			(0.021)	(0.034)	(0.018)
Controls and FEs	Yes	Yes	Yes	Yes	Yes
Observations	18,763	18,763	18,608	9,376	9,232
Adj. R^2	0.715	0.716	0.718	0.612	0.287

Panel D: Measures of patent novelty

Dependent Variables:	*Originality*	*Generality*	*Innov. Search*	$ln(1+N^{Top10\%})$	$ln(1+N^{NewClass})$
	(1)	(2)	(3)	(4)	(5)
SOL	0.267***	0.110***	0.114***	0.861***	0.411***
	(0.026)	(0.023)	(0.027)	(0.101)	(0.066)
IO	0.002	0.013	0.053***	−0.218***	−0.025
	(0.010)	(0.009)	(0.012)	(0.058)	(0.030)
SIF	−0.050	0.017	−0.050	0.211*	0.027
	(0.036)	(0.031)	(0.036)	(0.116)	(0.083)
$ln(SpillTECH)$	0.036***	0.032***	0.059***	0.020	0.132***
	(0.004)	(0.003)	(0.004)	(0.014)	(0.010)
$ln(SpillSIC)$	0.000	−0.002	0.005**	−0.026***	−0.005
	(0.002)	(0.002)	(0.002)	(0.009)	(0.006)
Controls and FEs	Yes	Yes	Yes	Yes	Yes
Observations	18,608	18,608	18,608	18,608	18,608
Adj. R^2	0.125	0.468	0.115	0.532	0.199

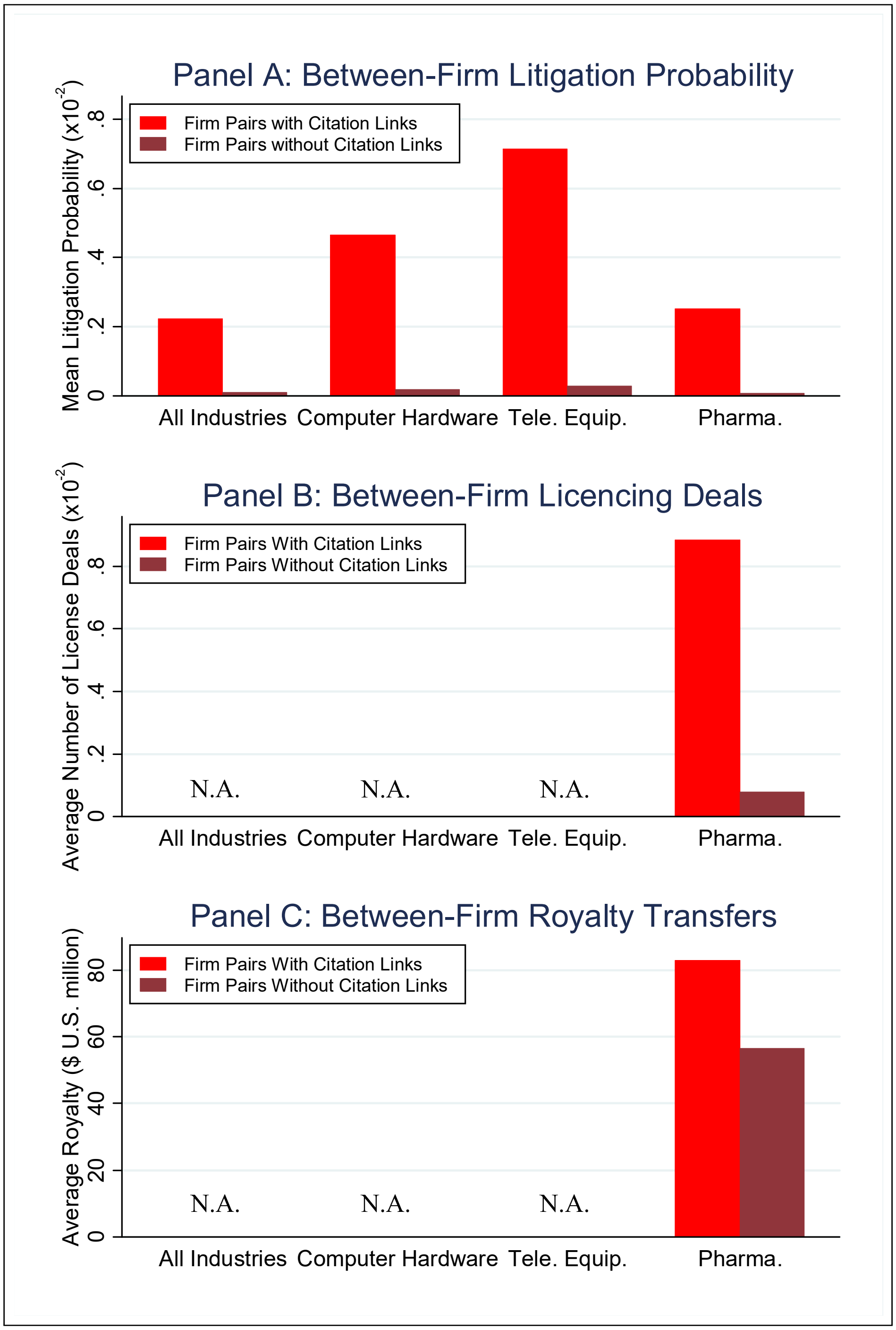

Figure 1: This figure compares the between-firm patent litigation probability (Panel A), number of licensing deals (Panel B), and royalty transfers (Panel C) for listed firm pairs with citation links and those without any citation link in the 10 years leading up to the litigation. The litigation cases are drawn from the USPTO Litigation database for the period 1992–2007. The licensing deals and royalty data are from the Cortellis database, which covers only pharmaceutical firms. Each year we form intra-industry firm pairs (based on the Fama-French 49 industry classification scheme) of all U.S. listed firms with at least one patent in the patent database and sort them into pairs with at least one patent citation link and pairs without any such link. In Panel A, the litigation probability is 0.223% for the pairs with citation links and 0.010% for the pairs without in the full sample. The corresponding probabilities are 0.466% and 0.019% for the computer hardware sector, 0.715% and 0.030% for the telecommunication equipment sector, and 0.253% and 0.008% for the pharmaceuticals sector. In Panel B, the average number of patent licensing deals is 0.0089 for firm pairs with citation links and 0.0008 for the pairs without. In Panel C, conditional on firm pairs with licensing deals and royalty value available, the royalty value is USD 82.92 million for the pairs with citation links and USD 56.45 million for the pairs without. The label “N.A.” in Panels B and C indicates that the data are not available for the respective industries.

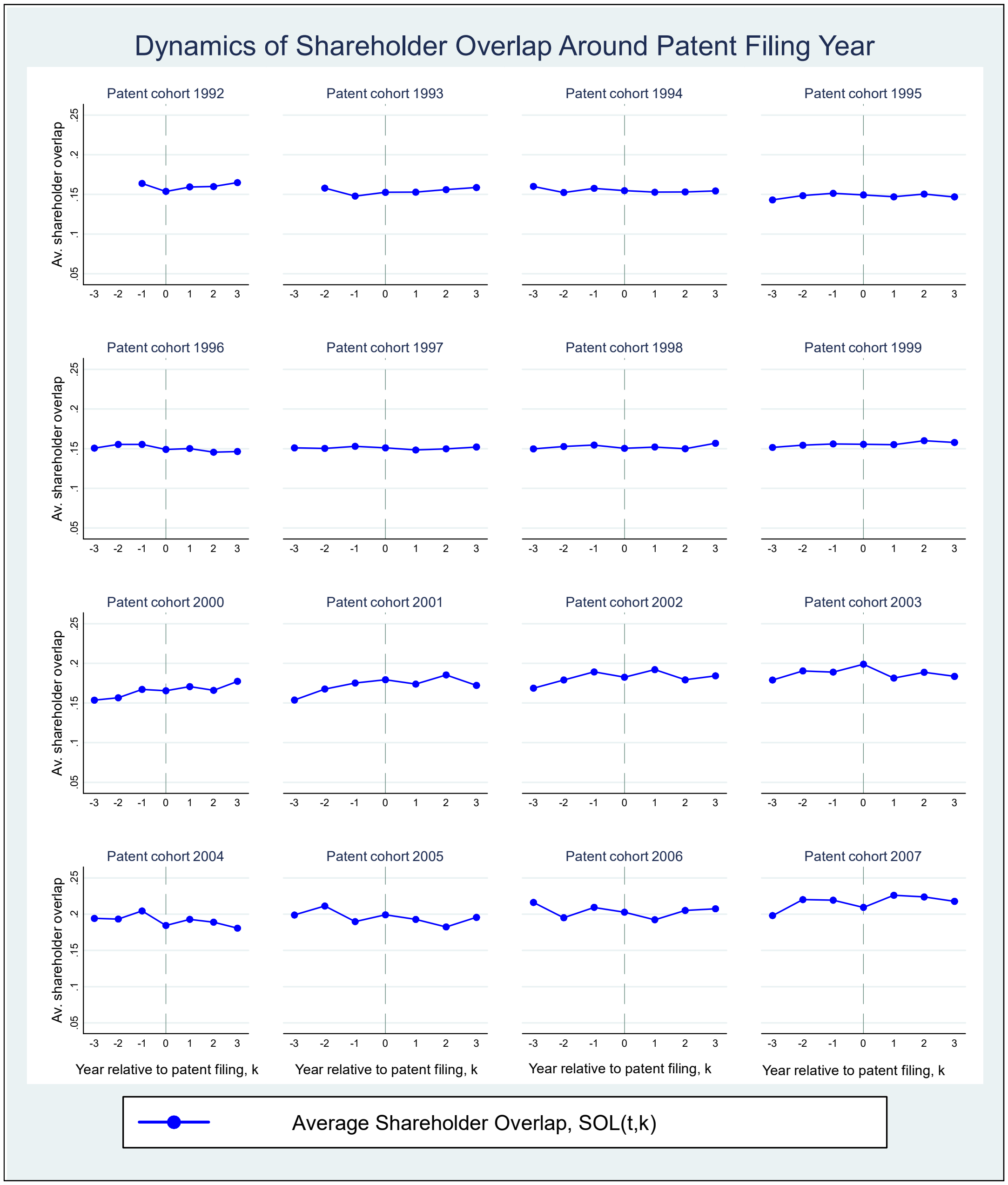

Figure 2: We plot the dynamics of shareholder overlap around the patent-filing year for 16 yearly patent cohorts, which are patents filed in years $t = 1992, 1993, ..., 2007$. The blue line in the graph describes the average shareholder overlap $\overline{SOL}(t, k)$ between the innovating firm and other firms owning complementary upstream patents from three years prior to the patent filing year to three years after the filing (i.e., $k = -3$ to 3), with the patent filing year denoted by $k = 0$.

Internet Appendix

(Not for Journal Publication)

On the Benefits of Cross-Firm Ownership for Cumulative Innovation

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Appendix A. Variable Definitions

Variable	Description
$CITES_{s,t}$	Total future citation count for the cohort of patents filed by firm s in year t. Only those patents that are subsequently granted by USPTO are included in our sample. [Source: Kogan et al., 2017; Hall et al., 2001]
$N_{s,t}$	Number of patents filed by firm s in year t. Only those patents that are ultimately granted are included in our sample. [Source: Kogan et al., 2017]
$\overline{cites}_{s,t}$	Average future citation count per patent for the cohort of patents filed by firm s in year t. [Source: Kogan et al., 2017; Hall et al., 2001]
$CITES^F_{s,t}$	Total filtered future citation count for the cohort of patents filed by firm s in year t. It removes from $CITES_{s,t}$ citations from the upstream firms cited in the patent filings of the downstream firm s in year t. [Source: Kogan et al., 2017]
$CITES\_3yr_{s,t}$	Three-year citations received by the cohort of patents filed by firm s in year t. For each patent, we count citations received during the calendar year of patent grant and the three subsequent years. [Source: Kogan et al., 2017; Hall et al., 2001]
$CITES\_3yr^F_{s,t}$	Filtered three-year citations received by the cohort of patents filed by firm s in year t. It removes from $CITES\_3yr_{s,t}$ citations from the upstream firms cited in the patent filings of the downstream firm s in year t. [Source: Kogan et al., 2017; Hall et al., 2001]
$R\&D\ Exp/Assets_{s,t}$	The ratio of $R\&D$ expenditure (XRD) in year t to total assets (AT) in year $t-1$. [Source: CRSP/Compustat Merged Database (CCM)]
$Patent\ \ Dollar\ Value_{s,t}$	The aggregate estimated market value of all patents filed by firm s in year t, measured in millions in 1982 dollars. [Source: Kogan et al., 2017]
$Originality_{s,t}$	Average originality score for patents filed by firm s in year t. The originality of a patent is defined as a Herfindahl Hirschman Index (HHI) based on the distribution of cited patents across the three-digit patent classes. [Source: Our own calculation]
$Generality_{s,t}$	Average generality score for patents filed by firm s in year t. The generality of a patent is defined as an HHI based on the distribution of citing patents across the three-digit patent classes. [Source: Our own calculation]
$N^{Top10\%}_{s,t}$	Number of patents filed by firm s in year t that belong to the top 10% most cited patents in their respective patent class. [Source: Our own calculation]
$N^{NewClass}_{s,t}$	Number of new class patents filed by firm s in year t. A new class patent in year t is defined as a patent belonging to a patent class in which the firm has never filed patents before. [Source: Our own calculation]
$Innov.\ Search_{s,t}$	Innovative search score of firm s in year t. Following Manso et al. (2019), we construct the measure as $Innovative\ Search_{s,t} = 1 - \frac{T_{s,t}\ T^{5yr\prime}_{s,t-1}}{(T_{s,t}\ T'_{s,t})^{1/2}(T^{5yr}_{s,t-1}\ T^{5yr\prime}_{s,t-1})^{1/2}}$. $T_{s,t} = (T_{s,t,1}, T_{s,t,2}, ..., T_{s,t,K})$ and $T_{s,t,k}$ denotes the fraction of the firm's patents filed in year t that are in technological class $k \in [1, K]$. $T^{5yr}_{s,t-1} = (T^{5yr}_{s,t-1,1}, T^{5yr}_{s,t-1,2}, ..., T^{5yr}_{s,t-1,K})$, and $T^{5yr}_{s,t-1,k}$ is the fraction of the firm's patents filed during the period $t-5$ to $t-1$ that are in the technological class k. [Source: Our own calculation]
$Litigation_{s,m,t}$	A litigation dummy with a value of 1 if firm s is a treatment firm (which is subject to patent litigation in year t), and zero otherwise. Each treatment firm is matched to a control firm. The two firms form a matched firm pair m. [Source: LitAlert Database and Public Access to Court Electronic Records (PACER)]

Variable	Description
$PSOL(p, p_u)$	Pairwise shareholder overlap $PSOL(p, p_u)$ between patent p's filing firm and the filing firm of its upstream patent p_u. It is measured according to Eq.(1). [Source: Kogan et al., 2017; Thomson Reuters 13F]
$sol_{p,t}$	Shareholder overlap for patent p, filed in year t. It is the average of $PSOL(p, p_u)$ across all upstream patents (p_u, $u = 1, 2, .., N_u$) cited by patent p. In cases where multiple upstream patents are owned by the same firm, we aggregate their citation count and treat them as one single patent.[Source: Kogan et al., 2017; Thomson Reuters 13F]
$cites_{p,t}$	Total number of future citations received by patent p, filed in year t. [Source: Kogan et al., 2017]
$SOL_{s,t}$	Shareholder overlap for firm s in year t. It is the average of $sol_{p,t}$ across all patents p filed by firm s in year t. [Source: Kogan et al., 2017; Thomson Reuters 13F]
$SOL\_Ded_{s,t}$	Shareholder overlap of dedicated investors for firm s in year t. It is the same as $SOL_{s,t}$ except that only the overlapping shares of dedicated investors are counted. At the end of each year, we sort all institutional investors by the HHI (in descending order) and churn ratio (in ascending order). We label investors in the top 50% of both the HHI sort and the churn ratio sort (i.e., high concentration and low turnover) as dedicated investors and the remaining investors as non-dedicated investors. The HHI is calculated as the sum of squares of each individual stock's weight in the investor's equity portfolio. The churn ratio for investor i in year t is calculated following Gaspar et al. (2005). [Source: Kogan et al., 2017; CRSP and Thomson Reuters 13F]
$SOL\_NonDed_{s,t}$	Shareholder overlap of non-dedicated investors for firm s in year t. It is defined in an analogous way to $SOL\_Ded_{s,t}$. [Source: Kogan et al., 2017; CRSP and Thomson Reuters 13F]
$SOL\_Placebo1_{s,t}$	First placebo shareholder overlap measure for firm s in year t. It is constructed in the same way as $SOL_{s,t}$ except that we replace every cited upstream firm with a *similar* firm that is *not* cited by the downstream firm s in the patent application year t. A placebo firm is chosen based on the criteria that it must have the same four-digit SIC code as the true upstream firm and that it has the shortest Euclidean distance from the upstream firm in terms of total assets and number of patents filed during $t-4$ to t. Both firm-level measures are log-transformed and scaled by their respective four-digit industry average. The Euclidean distance between firm $X = (X_{Assets}, X_{Patents})$ and $Y = (Y_{Assets}, Y_{Patents})$ is defined as $\sqrt{(X_{Assets} - Y_{Assets})^2 + (X_{Patents} - Y_{Patents})^2}$ [Source: Kogan et al., 2017; CRSP/Compustat Merged Database (CCM)]
$SOL\_Placebo2_{s,t}$	Second placebo shareholder overlap measure for firm s in year t. It is constructed in the same way as $SOL\_Placebo1_{s,t}$ except that the placebo firms are matched to the true upstream firms based on their technological proximity. Following Bloom et al. (2013), we measure technological proximity between a true upstream firm u and a placebo firm x by $\frac{T_u T_x'}{\sqrt{T_u T_u'}\sqrt{T_x T_x'}}$, where $T_u = (T_{u,1}, ..., T_{u,K})$ and $T_x = (T_{x,1}, ..., T_{x,K})$. $T_{u,k}$ denotes the ratio of the number of patents filed by firm u in technological field $k \in [1, K]$ in the past three years to the total number of patents it filed during the same period. $T_{x,k}$ is defined analogously. The chosen placebo firm features the greatest value in the technological proximity measure among all firms not cited by the downstream firm in the given year. [Source: Kogan et al., 2017]

Variable	Description
$SIF_{s,t}$	Shareholder innovation focus for firm s in year t. In the first step, we define for each listed firm s' the *firm innovation focus* (FIF) as the ratio of the future citation count of all patents filed by firm s' in year t to the industry average during the same period. In the second step, we account for all institutional investors i in firm s and calculate their respective *investor innovation focus* (IIF) as the value-weighted average *firm innovation focus* for all stocks s' in their respective investment portfolios except for stock s itself at the end of year t. In the third step, the *shareholder innovation focus* (SIF) for firm s is defined as the value-weighted average of investor innovation focus for all shareholders i in firm s at the end of year t, with each investor i being weighted based on their relative investment value in the firm. [Source: Kogan et al., 2017; CCM]
$SOL\_HHI_{s,t}$	Average HHI of shareholder overlap concentration for firm s in year t. For each patent p filed by firm s in year t, we identify all the overlapping shareholders $i \in I_{p,pu}$ who have a joint equity stake in firm s and the firm owning the upstream patent p_u. We then calculate $hhi_{p,p_u,t}$ as the HHI based on the overlapping ownership share of each overlapping shareholder $i \in I_{p,pu}$, with the ownership measured at the end of year t. $WHHI_{s,t}$ is the average of $hhi_{p,p_u,t}$ across all patents p owned by firm s and their respective upstream patents p_u [Source: Kogan et al., 2017; Thomson Reuters 13F]
$Private\ Patent\ Share_{s,t}$	Average proportion of private upstream patents for firm s in year t. For each patent p filed by firm s in year t, we calculate the share of privately owned upstream patents. We then average this private patent share across all patents filed by firm s in year t. [Source: Kogan et al., 2017]
$IO_{s,t}$	Aggregate institutional ownership percentage of firm s in year t. It is the ratio of the number of shares held by institutional investors to the total number of shares outstanding for firm s at the end of year t. [Source: Thomson Reuters 13F and CCM]
$IO^{SOL}_{s,t}$	Overlapping institutional ownership of firm s in year t. For each patent application year t, we identify all *overlapping shareholders* that hold joint equity stakes in firm s and its upstream patent-owning firms. $IO^{SOL}_{s,t}$ measures the ratio of the total number of shares held by overlapping institutional shareholders to the total number of shares outstanding for firm s at the end of year t. [Source: CRSP and Thomson Reuters 13F]
$IO^{NOL}_{s,t}$	Non-overlapping institutional ownership of firm s in year t. For each patent application year t, we identify all *overlapping shareholders* that hold joint equity stakes in firm s and its upstream patent-owning firms. The remaining shareholders of firm s are identified as *non-overlapping shareholders*. $IO^{NOL}_{s,t}$ measures the ratio of the total number of shares held by non-overlapping institutional shareholders to the total number of shares outstanding for firm s at the end of year t. [Source: Thomson Reuters 13F and CCM]
$Assets_{s,t}$	Total assets value (AT) of firm s in year t, measured in USD millions. [Source: CCM]
$K/L_{s,t}$	Capital ($PPENT$) to labor (EMP) ratio for firm s in year t. [Source: CCM]
$R\&D\ Stock_{s,t}$	Cumulative R&D investment of firm s in year t. Following Hall et al. (2005), we measure $R\&D\ Stock_{s,t}$ as $R\&D\ Expenditure_{s,t} + 0.85 R\&DStock_{s,t-1}$. [Source: CCM]
$Leverage_{s,t}$	Leverage ratio for firm s in year t, defined as long-term debt ($DLTT$) divided by total assets (AT). [Source: CCM]

Variable	Description
$MktCap_{s,t}$	Market capitalization value for firm s in year t, which is measured at the end of the year in USD thousands. [Source: CRSP]
$Past\ Return_{s,t}$	The buy-and-hold stock return of firm s over the past 12 months before the patent litigation. [Source: CRSP]
$PatentStock_{s,t}$	Number of patents filed over the past five years. [Source: Our own calculation]
$TobinQ_{s,t}$	Tobin's q of firm s in year t, which is calculated as the sum of stockholders equity(SEQ), deferred tax and investment tax credit ($TXDITC$) minus preferred stock ($PSTKL$), then divided by the product of fiscal-year end stock price ($PRCC\_F$) and common shares outstanding ($CSHO$). [Source: CCM]
$SpillTech_{s,t}$	Technology (or knowledge) spillover from other firms for firm s in year t. It is the technological proximity-weighted sum of $R\&D\ Stock$ of all firms in year t except firm s. Technological proximity between firms m and s is defined by $\frac{T_m T_s'}{\sqrt{T_m T_m'}\sqrt{T_s T_s'}}$, where $T_m = (T_{m,1}, ..., T_{m,K})$ and $T_s = (T_{s,1}, ..., T_{s,K})$. $T_{m,k}$ denotes the ratio of the number of patents filed by firm m in technological class $k \in [1, K]$ over the whole sample period to the total number of patents it filed during the same period. $T_{s,k}$ is defined analogously. [Source: Kogan et al., 2017; CCM]
$SpillSIC_{s,t}$	Product market rivalry effect of $R\&D$ for firm s in year t. It is the product market proximity-weighted sum of $R\&D\ Stock$ of all firms in year t except firm s. Product market proximity between firms m and s is defined by $\frac{X_m X_s'}{\sqrt{X_m X_m'}\sqrt{X_s X_s'}}$, where $X_m = (X_{m,1}, ..., X_{m,Q})$ and $X_s = (X_{s,1}, ..., X_{s,Q})$. $X_{m,q}$ denotes the share of firm m's sales in industry $q \in [1, Q]$ relative to its total sales during the year, averaged over the whole sample period. Industries are defined by four-digit SIC codes. $X_{s,q}$ is defined analogously. [Source: Kogan et al., 2017; CCM]