Patent Acquisition, Investment, and Contracting

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ABSTRACT

Numerous works have examined the finance-related implications of intellectual property that is generated internally or acquired through M&A activity. The transfer of intellectual property via the secondary market for patents has received less attention. This paper fills that gap by asking how patent acquisitions interact with firm investment policy. I find that patent acquirers subsequently invest in more R&D, increase internal patenting, and eventually make new investments in CAPX. Firms with more technological expertise and investment opportunities acquire more patents. Patent sales are the dominant type of contract and maximize investment incentives; patent licenses frequently contain royalties, which induce underinvestment problems. Nevertheless, licensing can be explained in part by financial and strategic considerations. Licensing is more likely when buyers become financially constrained, when revenue can be shifted to low tax sellers, and when the buyer is a competitor acquiring rights to a valuable patent. Overall, these results suggest patent acquisitions are motivated by the pursuit of investment synergies, rather than innovation substitution, commercialization motives, or legal threats.

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I Introduction

The secondary market for patents—buying and licensing patents—involves over 20% of all patents granted since 1980 and is 5.6 times larger than the number of patents involved in mergers. Despite its transaction volume, the buying and selling of patents has been understudied. This lack of attention is surprising given the voluminous literature analyzing the interactions between financing and intellectual property and the acquisitions of firms with patents. Thus, this paper focuses on the fundamental question of whether firms are in secondary patent markets to substitute or complement for their own investments in research.

Existing literature provides ambiguous guidance on whether patent acquirers will subsequently invest more or less in R&D. R&D might decrease for three reasons. First, patent acquisitions could simply substitute for internal innovation. Second, patent acquirers driven by commercialization motives could shift investment away from R&D (Phillips and Zhdanov (2013)). Third, post-acquisition innovation may be stifled by the acquiring firm (Seru (2014) and Gompers, Lerner, and Scharfstein (2005)). Alternatively, R&D might increase if firms acquire patents that have synergies with firm capabilities (Bena and Li (2014) and Hoberg and Phillips (2010a)), patents that blocked innovative efforts (Williams (2010)), or patents that allow firms to pursue investment opportunities (Rhodes-Kropf and Robinson (2008)).

Thus, the relationship between patent acquisitions and future R&D is an empirical question. To examine it in a systematic way, I construct a new patent-transaction level dataset that links the names of 1.1 million patent buyers and sellers to Compustat. Transaction data comes from the USPTO's Patent Assignment Dataset (PAD), which covers all US patent assignments for the 1980-2014 period. Matching these patent transactions to firm characteristics overcomes the central challenge that has stunted research on the patent market.

The final firm-linked patent transaction level dataset contains 1.4 million patent sales and licenses and reveals that participation of public firms in the secondary patent market is widespread. In fact, about 64% of all Compustat firms and 38% of firm-years participate in patent transactions. Additionally, innovation among public firms is almost entirely accounted for by years in which firms are active in the secondary patent market: These firm-years account for 92% of all patent grants to public firms and 88% of all Compustat R&D expenditures during the sample period.

Figure I shows that the patent market is playing an increasingly large role in the economy. The annual fraction of public firms buying or selling patent rights nearly tripled between 1980

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and 2010. By 2010, the majority of firms used the patent market each year. The implication of the large, growing, and widely used patent market is that the gap in knowledge regarding the role of patent transactions in firm investment decisions is increasingly important. This paper, by linking market transactions to firm data, represents an initial step towards bridging that gap.

[Insert Figure I about here]

To evaluate whether patent acquisitions are followed by increases or decreases in R&D, I construct a firm-year panel with variables that capture a firm's yearly activity in the secondary patent market. Specifically, I measure the citation weighted number of patents in which a firm acquires rights via purchase or license, and likewise for patents in which a firm divests rights. I add these measures to a standard investment regression which controls for determinants of investment policy and unobserved heterogeneity at the firm and industry-year level. I find that doubling patent acquisitions in a year from 1.5 to 3 is associated with one year ahead R&D that is 7.9 percentage points higher.[1] This relationship is large: roughly 72% of the sample mean R&D rate of 10.7%.

This finding indicates that, on average, patent acquisitions complement future R&D. To support this interpretation, I examine the broader pattern of firm innovation and investment. I find that acquiring firms receive more patents in the following years. These patents build on a wider array of technology fields and earn more citations in the long run. This is inconsistent with the notion that innovation is stifled following acquisitions in the patent market. This is consistent, however, with patent acquisitions and internal R&D being complementary and suggests that acquired patents increase productivity—a possibility I explore in later tests.

To add credence to the main interpretation, I examine physical investment (CAPX) and advertising, which are investments plausibly related to commercialization. Tests show that patent acquisitions do not predict CAPX or advertising spending in the short run. This finding runs counter to the commercialization motive at the heart of a substitution prediction. The lack of comovement among all types of investment also indicates that higher post acquisition R&D is not due to an idiosyncratic shock to all investment opportunities, but is due instead to the patent acquisition itself. Investigating long run relationships, I find that

[1] Among firm-years with positive acquisitions, increasing acquisitions from 1.5 to 3 is equivalent to moving from the 30th to the 45th percentile of acquisitions. Among all observations, including those without acquisitions, this move is equivalent to moving from the 75th to the 80th percentile of the distribution.

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physical investment is significantly higher three and four years after an increase in patent acquisitions. This delayed increase, which occurs simultaneously to a detectable increase in citations, is consistent with R&D projects maturing into operations with a delay.

The overall pattern of innovation, R&D, and physical investment strongly support the case of a complementary relationship with R&D and conversely, do not support a view of patent acquisitions driven strictly by innovation substitution, commercialization, or legal hold up.[2] Instead, the evidence suggests that patent acquisitions facilitate R&D.

In a second set of tests, I offer evidence that firms with more plausible research and investment synergies acquire more patents, which supports the notion that patent acquisitions facilitate R&D. To do so, I pose several explanations for higher R&D following acquisitions and test whether they determine participation in the patent market. I find that a one standard deviation increase in technological expertise measured by intangible capital stock and patent stock are associated with increases in patent acquisitions of 59% and 25%, respectively. Moreover, a one standard deviation increase in investment opportunities measured by Total Q and sales growth are associated with 4% and 3.3% increases in acquisition activity. These results lend credence to the notion that research complementarities arise from technological synergies, as found by Bena and Li (2014) in the context of mergers.[3] Conversely, I find no evidence that patent acquisitions are related to competitive threats or the amount of patents that peer firms are litigating. The lack of a relationship between patent acquisitions and litigation might be due to seller factors; sellers in litigious industries substantially reduce patent sales. I find that patent sellers have more intellectual capital, as expected, but deteriorating performance in the product and technology markets. This suggests that patent transactions reallocate patent rights to firms more able to exploit them.

In the final set of tests, I ask whether the patent transaction itself is structured to improve investment incentives. I focus on whether patent rights are acquired by purchase or license. The distinction between these two contract types is important, as the choice essentially allocates the ownership and cash flow rights of the patent going forward. In a license, ownership of the patent is retained by the seller but used by the buyer. In a sale, the patent transfers to the new owner following a one-time exchange of cash. Thus, the contract sets firm boundaries, and this setting offers a novel way to understand the dynamics that contribute

[2] Survey evidence in Feldman and Lemley (2015), concentrating on patent licenses, suggests that patent transactions are a sideshow. The implication of a "sideshow" view of transactions is that patent acquisitions are unrelated to future R&D and CAPX.

[3] See also Hoberg and Phillips (2010a) and Rhodes-Kropf and Robinson (2008).

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to organizational form. The primary difference between purchase and license agreements, besides ownership, is that patent licenses often contain royalties calculated as a share of revenue or income. Unlike with leases of physical capital, royalties effectively transfer equity (variable rents) in products based on the patent from the buyer to the seller. Thus, licenses decrease the buyer's incentives to invest and induce underinvestment. Consistent with that notion, I find that patent sales are the dominant type of contract, comprising nearly 98% of transactions.[4]

While sales comprise the bulk of transactions in the data, analysis of the contractual choice reveals that financial considerations justify the use of licensing. I specify an empirical contracting model that estimates the likelihood of a transaction being a license agreement and find that licensing is more likely when the buyer is financially constrained, which extends the Eisfeldt and Rampini (2009) finding regarding physical capital leases to patent licensing. I also find that licensing is more likely when the seller is the low tax party. This result can be explained by the use of royalties in order to reduce the combined taxes incurred by the buyer and seller. This allocation tendency—ownership by the low tax party—runs counter to intuition developed in studies of capital leases, wherein the high tax party tends to own equipment because of the use of depreciation tax shields.

Lastly, I show that strategic considerations also justify licensing. Classic contracting models ignore strategic competition and predict that as the productivity of a transacted patent increases, underinvestment following a license agreement is exacerbated. This, in turn, causes the transaction surplus of licensing to decline relative to purchasing. Thus, a key prediction of these models is that licensing is decreasing in patent productivity. Yet, I find the opposite correlation in the data. I measure preexisting citations between acquirers and the acquired patents. Preexisting acquirer citations show that acquirers have existing research capacity directly related to the patent and thus reveal a type of complementarity. This complementarity captures a dimension of buyer-specific value or productivity. I find that as acquirer-patent citation links increase, licensing agreements become more probable.[5] I hypothesize that product market considerations strongly mediate this "puzzling" result. The idea is that, all else equal, sellers prefer to maintain control over valuable patents,

[4] All contract level analysis is based on the subset of transactions with only one buy-side firm and one sell-side firm. This rules out cross-licenses and bundled sales, which have substantively different contracting dynamics.

[5] Moreover, other measures of ex-ante patent value are positively and significantly related to licensing propensity. This relationship holds whether patent value is measured using the stock market impact at grant date (following Kogan, Papanikolaou, Seru, and Stoffman (2012)) or pre-transaction citations.

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but especially when dealing with product market rivals. Indeed, I find that acquirer-patent complementarities are positively related to licensing only among transactions between firms in the same industry. In fact, when a transaction is between firms in different industries, transactions with more acquirer-patent citations are more likely to be sales, as predicted by models that focus on investment optimization, such as Aghion and Tirole (1994).

Altogether, this paper makes three main contributions. First, this paper highlights the importance of the secondary patent market and its relevance for corporate finance. In linking patent market transactions to public firms, I extend the literature on patent transactions by directly examining corporate investment policy. In doing so, I add to the growing innovation-to-investment literature by showing that research investment is higher after acquiring external innovation. As a whole, the findings do not support the view that patent acquisitions are driven strictly by commercialization or innovation substitution, nor do they support the view that patent transactions are a legal sideshow resulting in few products. Rather, patent acquisitions seem to facilitate research efforts. This conclusion extends recent studies in corporate finance showing firms increase innovation after accessing external intellectual property via mergers (Bena and Li (2014)) or corporate venture capital (Ma (2015)) to the largest market for intellectual capital—the secondary patent market.

Second, in examining how firm boundaries are set by the contracting decision, I extend the finance literature on the buy or lease decision for tangible capital to intangible capital.[6] Like tangible capital leases, licensing allows sellers to extend a type of financing. Unlike tangible capital leases, however, the contracting parties to a patent transaction allocate the patents to the low tax party. This allocation rule reduces depreciation tax shields but generates tax savings on the portion of income subject to royalty payments. Thus, the key lesson of the buy or lease literature does not apply directly to patent transactions. This contracting analysis also extends the vertical integration literature by highlighting the interaction between under-investment costs and strategic competition.[7] Finally, the contractual analysis highlights the strong dominance of contracts which maximize incentives to build on patents and innovation and thus relates to the financial literature on optimal innovation contracting.[8]

Third, a complementary relationship between patent acquisitions and R&D suggests that

[6] On tangible capital leasing, see, e.g., Smith and Wakeman (1985), Eisfeldt and Rampini (2009), Sharpe and Nguyen (1995), and Rauh and Sufi (2012).

[7] E.g., Aghion and Tirole (1994), Grossman and Hart (1986), and Hart and Moore (1990).

[8] E.g., Acharya, Baghai, and Subramanian (2014), Hackbarth, Mathews, and Robinson (2014), Manso (2011), and Robinson (2008).

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for the acquirer, the presence of the acquired patent was hindering follow-on research before the transaction. This finding sits at the heart of a debate about the role of patents in facilitating research. Whether patents reduce the rate of cumulative innovation is central to patent policy design and recent research on the topic has been cited in Supreme Court decisions. This literature focuses on how citations (either in patents or scientific publications) respond to the removal of intellectual property rights or surprise patent approvals. I complement these studies by directly examining research spending following patent transfers. This amounts to testing the impact of the removal of patents from competitors. My findings align with recent studies that find evidence that decreased patent litigation risk increases R&D (Mezzanotti (2015)) and increased intellectual property rights depress citations by about 30% (see Murray, Aghion, Dewatripont, Kolev, and Stern (2008) and Williams (2010)). Because these studies examine non-patent forms of protections, Sampat and Williams (2016) instead look at a quasi-exogenous variation in whether patents are granted for DNA sequences and find no evidence that a grant depresses subsequent citations to the same DNA sequence. Their finding can be reconciled with the evidence here if patents depress research by the most likely alternative user (leading to my results) but not firms with lower valuations of the patent (thus diluting the economy-wide impact which is the focus of Sampat and Williams (2016)).

The paper proceeds as follows. Section II presents the main results on investment following patent acquisitions. Section III examines the determinants of participation in the patent market. Section IV analyzes the contracting decision. Section V concludes.

II Patent market activity and investments

This section establishes the complementary relationship between patent acquisitions and R&D. Theories and related evidence on R&D investment following patent acquisitions are discussed in Section II.A. I introduce the main variables based on a new, US-economy wide patent transaction level dataset in Section II.B. Then, I specify and discuss the central test equation in Section II.C and present the main results in Section II.D. Finally, I discuss the interpretation of the findings in Section II.E.

A Theoretical tension and discussion

Efficient markets for tangible goods reallocate resources to their first best use, facilitating investment and growth. While research on the role of markets for physical goods is well

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developed, research on the market for ideas—especially in corporate finance—is still up and coming.[9] This gap in research is crucial given the role of patents in firm dynamics (such as financing investments and firm growth) and the role of R&D in theories of endogenous growth.[10]

Thus, this paper focuses on whether patent acquisitions complement or substitute for future R&D on average. This question, which focuses on market transactions and not the market itself, matters because it sits at the center of four important discussions. One, it relates to the large debate about the role of patents—either the firm's own patents or those of its competitors—in research and investment decisions.[11] Two, it relates to the discussion about whether the patent market eases R&D investment frictions.[12] Three, it relates to studies of vertical integration and particularly to studies focusing on the role of patents and technological know-how in merger decisions.[13] Four, it also relates to broader discussions about the nature of transactions and contracts in this large and growing market.[14] Despite the importance of each of these debates and the large bodies of research that accompany them, there is no study that investigates the role of patent acquisitions in R&D decisions. In lieu of direct evidence, we can look to related literatures for theoretical and empirical guidance about economic mechanisms that would lead to higher or lower R&D following patent acquisitions.

A reasonable starting point is the literature on cumulative innovation, which focuses in particular on how patents impact the R&D decisions others make. Because innovation is often cumulative, a patent held by an inventor might reduce or eliminate follow on research by others if any market friction prevents the transfer of rights between the inventor and others wishing to use the patent. In the absence of such a transaction, litigation risks (e.g. costs due to injunction and infringement) can maintain the patent holder's monopoly use over the patent. If patents do hinder research by others, then the implication in the setting of this paper—assuming firms buy patents that were blocking R&D—would be that patent acquisitions precede R&D increases. Yet, the rich theoretical literature in the area has produced ambiguous predictions (Sampat and Williams (2016)), and the most recent (and well

[9] Notable exceptions include Bena and Li (2014), Ma (2015), Serrano (2010), Seru (2014).

[10] On financing, see, for example, Cockburn and MacGarvie (2009), Hochberg, Serrano, and Ziedonis (2014), Hsu and Ziedonis (2008), and Mann (2015). On endogenous growth, see the classic article Romer (1990).

[11] See Hausman, Hall, and Griliches (1984) and Hall, Griliches, and Hausman (1986).

[12] See Ziedonis (2004).

[13] See Aghion and Tirole (1994), Hitt, Hoskisson, Ireland, and Harrison (1991), and Phillips and Zhdanov (2013).

[14] See Arora, Fosfuri, and Gambardella (2004) and Ahuja and Katila (2001).

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identified) empirical efforts disagree about the impact of intellectual property on follow on research.[15] In fact, if patents have positive technological spillovers (a la Bloom, Schankerman, and Van Reenen (2013)), then future patent acquirers might have follow on research in place before the acquisition with the expectation of a patent deal. When its follow on research matures, the project shifts from R&D to commercialization and continued infringement becomes more risky. This prompts the patent acquisition as R&D becomes secondary to commercialization.[16] Thus, this literature does not offer clear theoretical or empirical guidelines for the test I conduct.

Another related and growing literature that involves external patent acquisitions examines the role of patents in mergers. Mergers are more complicated transactions than patent acquisitions, but acquisitions of small technology firms (whose patents constitute a larger share of firm value) might approximate patent purchases. Exploring purchases of small firms, Phillips and Zhdanov (2013) outline a commercialization motive, wherein larger firms avoid an R&D race with smaller firms because they can acquire the smaller firm (and its R&D) and commercialize the target's innovation. If this finding applied to patent acquisitions, a commercialization motive would predict a substitute finding. Another explanation for decreased ex-post innovation comes from Seru (2014). He finds that acquirers stifle innovation of target firms and attributes this to the organizational structure of diversified acquirers. However, other papers in this literature offer contrasting implications. A leading example of this is Bena and Li (2014), which finds that mergers are more likely when the target's technology overlaps with the acquirer's. They argue that this represents synergies in technological expertise, and find that such synergies lead to more produced patents. Importantly, they do not directly examine post acquisition R&D choices.

A growing literature on patent transactions questions the nature of patent transactions and the role of non-practicing entities (colliqually, "patent trolls") in the patent market. In a survey of practitioners, Feldman and Lemley (2015) report that patent licenses lead to few new products. In effect, they find that firms paying patent licenses typically continue operations unaltered, even if the license demand comes from a non-troll. The implication of this hypothesis would be no change in R&D post acquisition.

Overall, the ambiguity of preexisting evidence, both theoretical and empirical, highlights

[15] See Galasso and Schankerman (2014), Murray, Aghion, Dewatripont, Kolev, and Stern (2008), Sampat and Williams (2016), and Williams (2010).

[16] On this point, see Arora (1995), Arora, Fosfuri, and Gambardella (2004), Kieff (2001), Gans, Hsu, and Stern (2002), Gans, Hsu, and Stern (2008).

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the need for this research. The remainder of this section presents the main results. After determining whether the primary relationship is one of complementarity or substitution, this paper will confront the challenge of assessing which channels are likely driving the relationship.

B Data and sample

The focus of this paper requires data on secondary patent market transactions. Thus, I begin by constructing a comprehensive set of patent sales and licenses. The USPTO Patent Assignment Dataset (PAD) contains records of 6.3 million patent assignments involving over 10.1 million patents between 1980 and 2014. I overcome two major hurdles to use this dataset. First, there are many reasons for recording a patent assignment.[17] I follow Serrano (2010) and Ma (2015) to define which assignments are sales and which are licenses. This step results in a dataset containing about 350,000 transactions with 1.4 million patents and 1.1 million names of buyers and sellers.[18] Second, I match the listed names of each assignee (buy-side of the transaction) and assignor (sell-side) to US public firm identifiers (GVKEY and PERMNO). This match allows systematic study of how patent transactions are related to firm characteristics.

The appendix describes the construction of the sample in detail, but the most important and novel step is the matching process to link the 1.1 million names of buyers and sellers to Compustat. I standardize the names and then create three auxiliary datasets to link the standardized PAD names to the standardized names of public firms. The first auxiliary dataset exploits the fact that the first assignment of a patent is often not a sale or license, but the assignment from the inventor to the employer firm. In fact, Marco, Myers, Graham, DAgostino, and Apple (2015) reports that these assignments account for over 82% of PAD assignments. For these 5.2 million assignment records, I merge in the firm identifier for the firm that was granted the patent (as listed in the NBER patent data project and Kogan, Papanikolaou, Seru, and Stoffman (2012)). This produces an exact map from the name of the assignee (the employer) in the PAD data to a firm identifier while bypassing the need to do string matching. Applying this PAD-name-to-firm-identifier map to the 1.1 million buyer and seller names accounts for about 50% of the matches I obtain. The second auxiliary

[17] According to Marco, Myers, Graham, DAgostino, and Apple (2015), which documents PAD, reasons for assignment include initial assignments from the inventor-employee to their employing firm, sales, corrections to the record, and security interests.

[18] Transactions can contain multiple patents and some transactions are cross-licensing deals or bundled sales involving multiple buyers and sellers.

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dataset is a comprehensive list of firm name variations compiled by the SEC with which I accept exact name matches. This second step accounts for about 10% of successful matches. Because these steps will fail to match a large number of firm name variations, I build a third auxiliary dataset containing pairs of standardized PAD names and names from the SEC list, along with similarity scores from several fuzzy match functions. Using a random sampling procedure, I pick an algorithm that designates accepted matches with a low false positive rate based on the different similarity scores. This step accounts for the remaining 40% of name to firm identifier matches. Overall, 66% of assignees and 60% of assignors are public firms.

At this stage, the dataset now contains patent sales and licenses along with firm identifiers for buyers and sellers. From this, I construct a firm-year panel with variables that capture activity in the secondary patent market. $PatAcq(CW)$ is the citation weighted sum of patents a firm acquires in a year and $PatDiv(CW)$ is computed similarly for patents a firm divests.[19] I merge these variables with Compustat to create a firm-year sample. All variables are defined in Appendix A. Utilities, government, and financial firms (SIC 49, 6, and 9) are excluded from the sample. Since the focus is on R&D expenditures, I restrict the main analysis to firms with active R&D programs as indicated by the Compustat variable XRD.[20]

Table I shows that participation in secondary patent markets is widespread. Over half of all firms (whether or not the firm has active R&D) acquire a patent at some point in their lifetime and a majority sell patent rights as well. Overall, nearly two-thirds of firms participate in the patent market. Most innovative activity and research in the US economy are done while firms are actively using the market: While firms only buy a patent in 28% of firm-years, these firm-years account for nearly 86% of patents granted to public firms and 81% of inflation adjusted R&D expenditures by public firms during the sample period. Sellers are innovative firms as well, as the 24% of firm-years that include a patent sale account for over 82% of patent grants and 77% of R&D expenses accured by public firms. Only 8% of patents are granted to firms not active in the patent market.[21]

[Insert Table I about here]

[19] Citations are measured pre-transaction for both variables.

[20] This impact of this restriction is assessed in Table IA.4 and discussed in Section II.D.

[21] The overlap between firm-years with transactions and grant reception is apparent at the industry level. Table IA.1 reports the fraction of patent acquisitions, divestitures, and patent grants by industry at the SIC2 and SIC3 levels. The broad pattern is industries that receive the most patent grants also buy and sell patent rights most often. High R&D industries are well represented, as most acquisitions are in electronic components, computer equipments, drugs, scientific instruments, and computing services.

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Figure I shows that the patent market is playing an increasingly large role in the economy. Over the entire sample, firms in 38% of their years buy or sell a patent and during that time, participation has nearly tripled. In the early 1980s, roughly a quarter of public firms were active participants in a market where less than 8,000 patents were bought by public firms. By the late 2000s, the annual fraction of firms in the market exceeded 50% and public firms acquired over 25,000 patents annually. Additionally, the patent market has become more involved in the economic life of patents. Patent grants in 2010 are three times more likely to be sold within four years than patents granted in 1980.

Research is increasingly highlighting the importance of patents for firm dynamics.[22] Within that context, the implication of the large, growing, and widely used technology market illustrated by Table I and Figure I is that the gap in knowledge regarding the role of patent transactions for firm investment (and other outcomes such as competition, financing policies, and productivity growth) is widening. This paper, by linking market transactions to firm data, represents an initial step towards bridging that gap.[23]

To ensure that correlation with R&D attributed to patent market purchases isn't confounded with the concurrent economy-wide shift towards obtaining patent grants or firms specific changes, I measure and control for internal innovation. Internal innovation—patents a firm receives directly from the USPTO, rather than acquired in purchases or mergers—is measured in terms of quantity (grants received), quality (citations), and originality (the span of technology fields a patent uses as reflected in the patents it cites).[24] I obtain data on patent grants through 2010 with firm identifiers from Kogan, Papanikolaou, Seru, and Stoffman (2012)[25] and augment this with citations data current through 2014 scraped from Google Patents. In addition to playing a key role as a control variable, how internal innovation changes following patent acquisitions will shed light on the nature and productivity of

[22] See Hall and Lerner (2010) and Kerr and Nanda (2014) for recent surveys of the large literature on the interaction between patents and financing.

[23] While researchers have used patent sales and other assignments in questions focusing on patent level outcomes or technology areas, this paper represents one of the first efforts to examine firm outcomes. Early contributions based on PAD data include Chesbrough (2006) and Serrano (2010). More recently, Fischer and Henkel (2012) examines the role of patent trolls in the patent market, Galasso, Schankerman, and Serrano (2013) estimates gains from trade in the market and shows patent sales reduce litigation risk, and Mann (2015) uses the dataset to explore how patents are used as collateral.

[24] I capture this by defining "Originality" as in Hall, Jaffe, and Trajtenberg (2001), where originality is assumed to capture patents synthesizing a wider variety of technologies into its patents. Specifically, for a patent, originality is one minus the HHI of technology fields the patent cites. Then, for a firm-year, originality is the average of this patent level measure across patent grants received that year.

[25] The dataset can be downloaded at https://kelley.iu.edu/nstoffma/.

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the research firms undertake.

[Insert Table II about here]

Table II describes the main regression sample, which differs from the universe of Compustat firms due to the sample requirement that firms have active R&D programs. Relative to all firms, firms in the sample do more R&D (11% to 4%),[26] less physical capital investment (6% to 7%), and have higher averages for all innovation measures. I examine the role of sample selection in Table IA.4. I find that, as expected if non-R&D firms are unlikely to pay large fixed costs to begin R&D programs, results become attenuated as the sample includes more firms for which R&D is irrelevant. Nevertheless, the conclusions are robust to different methods of treating missing R&D observations and various sample restrictions based on R&D.

C Methodology and Predictions

The economic question is whether patent acquisitions are complementary to or substitute for future R&D. Thus, the main specification is designed to directly estimate this relationship while addressing several complications. Specifically, on the firm-year panel, I estimate

$$\begin{aligned}\text{R\&D}_{i,j,t} = {} & \alpha_1 \times \text{Acquired Patent (Flow)}_{i,t-1} + \alpha_2 \times \text{Divested Patent (Flow)}_{i,t-1} \\ & + \alpha_3 \times \text{Internal Innovation (Flow)}_{i,t-1} + \beta X_{i,t-1} + \eta_i + \eta_{j,t} + u_{i,j,t} \end{aligned} \quad (1)$$

where firm i is in industry j in year t. R&D is normalized by lagged assets. The main variable of interest, Acquired Patent $(\text{Flow})_{i,t-1}$ is defined as $Log(1 + PatAcq(CW))_{i,t-1}$. Divested Patent $(\text{Flow})_{i,t-1}$ is similarly defined as $Log(1+PatDiv(CW))_{i,t-1}$. To ensure that the new measures aren't simply picking up firm specific shifts towards patenting, I control for the flow of internal innovation, defined as $Log(1+NewPatStock)_{i,t-1}$, where $NewPatStock$ is the sum of new internal grants and citations received by internally generated patents. $X_{i,t-1}$ includes a measure of Q (specifically, *Total Q*) and cash flow as is standard in the investment literature to control for variation in invetment opportunities and cash flow constraints.[27] To prevent firm size from driving coefficient estimates due to the denominator in the dependent

[26] Compustat averages are not reported in the table. For this statistic, I assume missing R&D equals zero whenever missing.

[27] See Fazzari, Hubbard, Petersen, Blinder, and Poterba (1988) and Erickson and Whited (2000). *Total Q* is from Peters and Taylor (2016) and is downloaded from WRDS. Peters and Taylor (2016) developed *Total Q* to explicitly account for intangible capital and show in a neoclassical framework that it proxies for intangible investment opportunities. Cash flow is measured as in Chang, Dasgupta, Wong, and Yao (2014).

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variable, $X_{i,t-1}$ also includes Log(Assets)$_{i,t-1}$. I standardize the controls in $X_{i,t-1}$ (Q, cash flow, and assets) to ease economic interpretation. Standard errors are clustered by firm.

Although the aforementioned theories make strong predictions regarding associations, it is relevant to also explore the challenges that get in the way of causal inference, and the steps I take to mitigate the most direct concerns. First, I tackle two forms of unobserved heterogeneity. To address unobserved heterogeneity due to economic conditions, I include industry-year fixed effects. These controls imply that the coefficients can not be explained by shifts in economic conditions at the economy or industry level, even if the shifts vary by industry over time. For example, a technology shock might increase growth opportunities for all firms in an industry, but this would be absorbed by the industry-year fixed effects. To address unobserved heterogeneity at the firm level, I include firm fixed effects. These controls imply that the coefficients are identified largely by within firm variation. For example, an estimated positive relationship between patent acquisitions and R&D can not be due to stable firm specific factors such as founder CEOs capable of synthesizing and building on new ideas. The combined set of fixed effects therefore accounts for time-invariant unobserved firm heterogeneity and time-varying industry heterogeneity. Second, I explicitly test for pre-trends and find no evidence of that patent acquirers systematically increase R&D prior to transactions. Specifically, firms that are already increasing R&D do not acquire more patents. Third, I relax the one period ahead model to allow for more flexible dynamic relationships. These tests, presented in Tables V and IA.5, show that the conditional increase in R&D the year after acquisitions is robust to dynamic consideration.

While these tests reduce likelihood of bias in the coefficient, I take additional steps to pin down the interpretation of complementarity. The preferred methodology, if feasible, is to exploit exogenous variation in patent acquisitions. This route, however, is challenging. Valid instruments must be associated with acquisitions (relevant) but conditionally unrelated to investment decisions (the "exclusion" condition). Relevant buyer specific factors and other demand factors are highly likely to impact R&D and investment decisions, and thus fail the exclusion condition. Seller factors that increase the supply of patents for purchase must not only be unrelated to the economic conditions that drive buyer investment decisions but also be related to purchasing decisions. Factors that satisfy both conditions are hard to identify.

Instead of an identification approach, I look to rule out alternative stories by examining the broader pattern of investment and innovation following acquisitions. In particular, I examine the evolution of investment in physical assets and advertising and innovation outputs

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(patent grants, patent citations, patent grant breadth). To do this, I replace the dependent variable R&D with, respectively, CAPX divided by lagged assets, advertising divided by lagged assets, Log(1+Grants)$_{i,j,t}$, Log(1+Cites)$_{i,j,t}$, and Originality$_{i,j,t}$. Each of Grants, Cites, and Originality are based only on internal innovation of a firm. In addition to short run responses, I estimate a dynamic specification to estimate long run relationships. The predictions I discuss and test below are summarized in Table III.

[Insert Table III about here]

In either case—complement or substitute—I expect the short run response of R&D to persist in the long run. Turning to CAPX and advertising, the commercialization hypothesis would predict immediate and long run increases following patent acquisitions. Alternatively, a complementary relationship would predict either no or negative response in CAPX and advertising in the short run, but a long run increase in CAPX as R&D projects begin to mature. A delay in the onset of increased CAPX and advertising supports the complementarity story, wherein the patent acquisition is an important event, for another reason: If the acquisition and increased R&D are simultaneously driven by an idiosyncratic shocks to investment opportunities not captured by Q, investment of all types is likely to comove.

Changes to output of internal innovation following patent acquisitions also shed light on the nature of R&D following these acquisitions. If acquisitions are complementary to research, perhaps because the patents have synergies with existing but untapped firm resources, changes in R&D policy (both the amount and project selection of R&D) would likely result in more patents and more patent originality, with or without a delay. If, instead, the relationship is substitutive, patent grants and citations might decline as resources are diverted away from research both in the short run and the long run. The diversion of research resources from R&D would likely result in subsequent firm patents leaning on a smaller array of technologies. This prediction is stronger if firms concentrate on incremental patents to protect the product.[28]

To examine the dynamic predictions about firm spending and innovation in the years

[28] This notion is in line with Bhide (2000), Gompers, Lerner, and Scharfstein (2005), and Seru (2014), who note that large firms and acquirers can suppress entrepreneurial spirit and ideas.

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following a patent acquisition, I specify a distributed lag model

$$y_{i,j,t} = \sum_{k=1,2,3,4} \Big(\alpha_{1,k} \times \text{Acquired Patent (Flow)}_{i,t-k} + \alpha_{2,k} \times \text{Divested Patent (Flow)}_{i,t-k} \Big) + \alpha_3 \times \text{Internal Innovation (Flow)}_{i,t-1} + \beta X_{i,t-1} + \eta_i + \eta_{j,t} + u_{i,j,t} \quad (2)$$

where three additional lags for *Acquired* and *Divested Patents* are included.[29] Coefficients on the first lag of acquired patents corresponds with short run predictions, while the additional lags correspond to the long run predictions. The summary in Table III includes predictions for coefficients on the additional lags in Equation 2.

D Main results

Table IV presents the estimation of Equation 1. Controlling for determinants of investment policy and unobserved heterogeneity at the firm and industry-year level, patent acquisitions are positively related to next period R&D in a statistically and economically significant way. Specifically, doubling acquisitions (a 100% increase) is associated with 7.9 percentage point increase in R&D investment (which is 72% of the sample mean R&D rate of 10.7%).[30] This sensitivity is large – roughly half of that of the 13.4 percentage point relationship with doubling successful internal innovation ($NewPatStock$). Further consistent with a complementary relationship, firms that acquire patents receive more patents in the following year (column 4) and these patents build on a wider array of technology fields (column 6). Moreover, firms do not spend more on commercializing activities, as there is no significant relationship with CAPX or advertising. None of these findings fit the predictions of the substitution case. Finally, a 100% increase in patent divestitures is related to statistically significant decreases in R&D and CAPX of 10.5 and 8.5 percentage points, respectively, providing additional support for the conclusion.

[Insert Table IV about here]

The estimates of the (standardized) control variables are sensible. Q is significantly and positively related to each type of investment (e.g. Peters and Taylor (2016)). Cash flow is

[29] As in the static model, I standardize Q, cash flow, and assets (included in $X_{i,t-1}$) to facilitate interpretation, and standard errors are clustered by firm.

[30] A 100% increase in acquisitions is a reasonable amount of variation to examine. The mean of the main (logged) acquisition variable is 0.85. Exponentiating it and subtracting one, this corresponds to acquiring 1.5 citation weighted patents in a year. Doubling this from 1.5 to 3, represents a move from the 30th to the 45th percentile of firm-years with positive acquisitions. Among all firm-years, i.e. including years with zero acquisitions, doubling from 1.5 to 3 represents a move from the 75th to the 80th percentile of the distribution.

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positively related with CAPX and significantly negatively related to R&D and innovation outputs. Investments are decreasing in firm size (assets) because investments are normalized by assets. Larger firms produce more patents across more fields—a one standard deviation increase in asset size is associated with a 62% increase in patent grants.[31] Following a 100% increase in internal innovation ($NewPatStock$), firms typically make more intangible investments. Such an increase is associated with R&D that is 13 percentage points higher, CAPX that is 18 percentage points lower, and 28% more patents grants.

Next, I estimate the distributed lag model of Equation 2 and present results for patent acquisitions and divestments in Table V.[32] Estimations show that innovation output is higher after acquiring patents. A 100% increase in patent acquisitions is associated with 0.6% more citations three years after the acquisition.[33] Such increases are large—they are more than 25% of the sample mean. Patent acquisitions are also related to large increases in CAPX three and four years later, but not immediately. Specifically, a 100% increase in acquisitions is related to percentage point increases in CAPX of 4.2 (t-stat of 2.15) in year three and 4.3 (t-stat of 1.97) in year four (relative to the sample mean CAPX of 6%). Across both tables, advertising generally has no statistical relationship with patent acquisitions. These results are consistent with R&D maturing into patented innovation and production in the long run.

[Insert Table V about here]

Overall, the complementary view is supported by the pattern of estimates. To further ensure that the central coefficient in the R&D model of Table IV is estimated accurately, additional evidence is reported in Appendix IA.B. Table IA.2 assesses different functional forms, more general fixed effects, and inclusion of additional patent activity controls. Table IA.3 examines different normalizations of R&D. Table IA.4 explores the sample selection criteria. Both the statistical and economic conclusions are robust to each of these tests.[34]

[31] The marginal effect is given by $exp(0.483) - 1 = 0.62$.

[32] Results for the dynamic model are robust to including four lags of all independent variables. Because this generates high variance inflation factors due to multicollinearity and does not change the conclusions, I keep the specified model. I also test the above lag model against nested models with fewer lags (e.g. $k = 1, 2, 3$). The results, reported in Table IA.5, reject the subcases with one and two lags, but do not reject a three lag model. I keep the four lag structure, as the conclusions match a model with three lags.

[33] Years two and four are positive but insignificant.

[34] One exception is when all firms—including those that disclose zero R&D and those that do not disclose R&D—are included in the sample. The correlation remains economically large but is not statistically significant. The reduced statistical relationship is expected since non-R&D firms are unlikely to pay large fixed costs to begin R&D programs even after acquiring patent rights.

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E Interpretation

The results strongly conform to expectations in the case of a complementary relationship with R&D and thus do not support a view of patent acquisitions driven strictly by commercialization, a desire to displace imitative R&D (i.e. buying the patent instead of making a similar one), or legal hold up. Moreover, because CAPX does not respond immediately, it is unlikely that the immediate increase in R&D is due to idiosyncratic shocks to investment opportunities not captured by Q.

Instead, the strong but delayed increase in CAPX suggests that the nature of the transactions is related to R&D programs which mature into physical investment and, presumably, products. Higher CAPX in the long run is thus indirect evidence that runs counter to the survey evidence in Feldman and Lemley (2015) suggesting patent transactions are a sideshow. The results here, however, are not directly comparable to Feldman and Lemley (2015), as their results concentrate on non-exclusive licenses used by non-practicing entities (commonly called "patent trolls") to extract payment from as many firms as possible. Patent sales, which constitute the majority of acquisitions in my dataset, are less likely to reflect the type of legal actions that lead to Feldman and Lemley's result. The reasoning for this claim is simple: Sellers can not target other firms for legal action with patents they no longer hold. This distinction contributes to the debate about the efficacy of market transactions by highlighting that contract form matters in assessing the nature of the transactions.

Higher innovation and research investment following patent purchases is supported by research in other contexts where firms obtain access to intellectual capital (e.g. Ma (2015) in the case of venture corporate capital; Bena and Li (2014) in the case of mergers). Relatedly, there is a large literature on cumulative innovation examining whether patent rights hinder related research. Among others, Murray, Aghion, Dewatripont, Kolev, and Stern (2008), Williams (2010), and Galasso and Schankerman (2014) report evidence that intellectual property decreases follow-on work (i.e. citations to patents and scientific publications) by around 30%. Recently, Sampat and Williams (2016) find no evidence of such a reduction. This can be reconciled with the evidence here if patents depress research by the likely eventual buyers but not firms with lower valuations of the patent. Such dispersion in the "hindering" effect is reasonable if firms with valuable patents have limited ability to litigate threats and therefore concentrate on reducing infringement at the firms most likely to benefit from infringement. This economic story could result both in my findings, where buying a patent is related to

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increases in research, and also the findings in Sampat and Williams (2016), where the overall hindering effect is diluted and near zero across the economy.

Given the consistent findings and corroborative evidence, the question is: What drives the complementary relationship in this setting? The literature on cumulative innovation suggests that the complementaries I find are driven by litigation risk. Long standing economic theory on the nature of R&D suggests another reason litigation risk reduces R&D: Much of R&D is intangible investments in highly skilled employees. If a firm reduces R&D and these employees leave, the firm loses the employees' knowledge capital. To avoid this, managers smooth increases in R&D spending (Hall, Griliches, and Hausman (1986) and Lach and Schankerman (1989)). Given the intangible nature of R&D spending, the threat of large damages, settlements, and injunctions from lawsuits can exacerbate the reluctance to increase R&D.[35] In buying a patent, a firm eliminates in part or in whole the litigation risk in a particular area and thus reduces the probability of having to reduce R&D in the future.

However, there are other potential channels for this complementary relationship. Buying patent rights might unlock new opportunities to build on and synthesize ideas. Additionally, patents can be useful in lowering the effective tax rate of a firm and thus the marginal cost of capital, which can prompt higher investments in research.[36] The next section looks to examine these channels by estimating the determinants of activity in the patent markets.

III Participation in patent markets

Why do firms buy and sell patent rights? Are the decisions related to factors that could drive the complementary relationship, such as synergies, competition, litigation, growth opportunities, or financing benefits? This section evaluates the determinants of participation in the secondary patent market and asks how these relationships inform our understanding of the complementary relationship established in the previous section. I also evaluate whether patent acquisitions are just another form of patent generation. Put differently, should we think of the motives in the secondary patent market as distinct from motives in patent generation?

[35] Irreversible investments increase the threat posed by injunctions. In NTP v. Research in Motion, the jury awarded NTP $33.5 million in damages. To avoid the possibility of injunction, Research in Motion, the maker of Blackberry mobile phones, settled for $612.5 million—approximately 18 times the jury award (Lemley and Shapiro (2006)).

[36] Dischinger and Riedel (2011), Karkinsky and Riedel (2012), and Sikka and Willmott (2010) describe and evaluate the tax shifting mechanism. Among others, Hall and Jorgenson (1969), Hall and Van Reenen (2000), Hall and Lerner (2010) and Bloom, Schankerman, and Van Reenen (2013) illustrate the role of taxes in R&D decisions.

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Section III.A introduces the cross sectional specification and the empirical hypotheses. Section III.B reports and discusses the findings. Section III.C examines within firm variation in the decision to buy and sell patents to assess sources of possible selection bias in the main results. Section III.D discusses the interpretation of the findings.

A Designing the cross sectional determinant tests

Which firms are most active in patent markets? Pulling from related literature to select theoretically motivated determinants of patent transactions, I estimate the following specification on the firm-year sample:

$$y_{i,j,t} = \beta_1 \times \text{Internal Innovation}_{i,t-1} + \beta_2 \times \text{Competition and Litigation}_{i,t-1} + \beta_3 \times \text{Growth Opportunities}_{i,t-1} + \beta_4 \times \text{Financial Factors}_{i,t-1} + \eta_{j,t} + u_{i,j,t} \quad (3)$$

The dependent variables $y_{i,j,t}$ are logged measures of patent acquisitions, divestitures, net acquisitions, and internal patents generated.[37] Industry by year fixed effects ($\eta_{j,t}$) absorb industry specific (and economy wide) time trends. Standard errors are clustered by firm.

Each of the independent variables are plausible causes of the complementary relationship. First, I include as controls for *Internal Innovation* the firm's stock of intangible capital (K_{INT}) and the firm's citation-weighted stock of internally generated patents (*PatStock (CW)*). Including these factors, established in the literature as powerful predictors of patenting, serves two purposes. One, the technical expertise embodied in these measures of intellectual capital compose an important source of potential synergies with the acquired patent. Firms with more intellectual capital should thus be more likely to purchase patents. Two, if patent purchases are simply analogues of patent generation, then these variables should be positively related to patent acquisitions with the same sign, significance, and magnitude as they predict patenting. The stock of intellectual capital and patents should also positively predict sales for the simple reason that patents can not be sold without producing patents.

I also include R&D ratio among the proxies for internal innovation. While the stock variables capture the amount of intellectual capital at a firm, the R&D ratio captures firm focus on research and is an established predictor of patenting (e.g. Hausman, Hall, and Griliches (1984) find a strong positive relationship). Thus, it is necessary to include it in the base model in order to compare the cross-sectional and within-firm determinants of patent

[37] In the table, "PatAcq" stands for $Log(1 + PatAcq(CW))$, "PatDiv" stands for $Log(1 + PatDiv(CW))$, "NetAcq" equals $PatAcq - PatDiv$, and "Grants" stands for $Log(1 + FlowGrants)$

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purchasing and patent generation. The relationship between pre-acquisition R&D intensity and acquisitions can inform two important questions. One, including R&D in within-firm tests (discussed later in Section III.C and reported in columns 5-8 of Table VI) provides a way to check for pre-treatment trends. Two, including R&D in cross-sectional tests establishes whether buyers, holding intellectual capital levels fixed, are more or less research focused. The relationship between the preexisting R&D intensity of a firm and purchasing decisions is subtly distinct from the main question of this paper (the role of previously acquired patents in R&D) and taps into a larger literature on how the nature of R&D affects the way firms acquire new knowledge. Firms with more focus on R&D might monitor technological opportunities better and have higher capacity to absorb knowledge, or have less need to acquire outside knowledge. Rationales for the former are provided by Arora and Gambardella (1994) and Cohen and Levinthal (1990). Rationales for the latter are provided by Arora, Belenzon, and Rios (2014), Hitt, Hoskisson, and Ireland (1990), and Katz and Allen (1982).

Second, I assess the role of competitive threats and litigation. If patents owned by other firms hinder valuable research and development efforts, then firms under higher threat levels have larger benefits from acquiring patents and therefore, they should consequently buy more patents. Conversely, firms facing larger threats should sell fewer patents. I include two variables to capture these forces. The first variable, *ProdMktFluidity*, is based on product descriptions in firm filings and captures dynamic shifts in competition, product offerings, and technology (Hoberg, Phillips, and Prabhala (2014)). The second variable, *Log(1+TechPeerLit)*, directly captures litigation in the technology space a firm occupies. This variable increases in the litigiousness of technology peers and, likely, expected litigation risk in a given technology field. I define technology peers as all pairs of firms that cite each other, and then count the number of patents of a firm's peers that appear in district court litigation over the prior five years.[38] Importantly, both variables are constructed to have considerable *within* SIC3 variation and can thus be identified even with the industry-year fixed effects.[39]

Third, I consider proxies for growth opportunities at a firm. Controlling for possible synergies due to the technological expertise of the firm, firms with unexplored growth op-

[38] Data on litigation comes from Henry, McGahee, and Turner (2013). Most patent litigation does not reach the district court level, and thus the cases that reach the district court level select on both the value of the dispute and the attitudes towards litigation of the parties involved. Therefore, while this mismeasures the raw number of disputes, it captures a large share of the total value of legal disputes in the area.

[39] *ProdMktFluidity* is based on the text based TNIC definition of peers developed in Hoberg and Phillips (2010b) wherein peers can change over time (unlike static SIC groups) and thus has large variation both within SIC3 and within firm. *TechPeerLit* is based on technology peers defined by citations, whereas SIC3 peers are defined by products and services.

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portunities should be more (less) likely to acquire (divest) patent rights. I argue that these growth opportunities compose the other dimension of possible synergies between the firm and patent. The three proxies I consider—*Total Q*, *Sales Growth*, and *Patent Growth*—examine different possible dimensions of growth opportunities. Peters and Taylor (2016) developed *Total Q* to explicitly account for intangible capital and show in a neoclassical framework that it proxies for intangible investment opportunities. *Sales Growth* and *Patent Growth* proxy for growth in the product market and technological environments, respectively, under the assumption growth expectations match recent history.

Fourth, I consider two financial components motivated by evidence from the field and theory. Financial constraints (*DelayCon*) could motivate increased patent sales to raise money (as in Pulvino (1998)).[40] Another potentially powerful motive in this setting is due to the role of patents as a tax management tool.[41] By placing patents in low tax subsidiaries and licensing the use of patents to high tax subsidiaries, income is shifted to the low tax subsidiary and taxes are reduced. This technique is at the heart of controversies including Google, Apple, and others. Thus, firms with higher marginal taxes (*MTR-BCG*, from Blouin, Core, and Guay (2010)) have more to gain from acquiring patents and less to gain from selling patents.

B Cross sectional determinants of patent market activity

Columns 1-3 of Table VI present the estimates of the cross sectional model of Equation 3. To ease interpretation, all dependent variables are standardized.

[Insert Table VI about here]

Column 1 assesses the drivers of patent acquisitions. I find no evidence that competitive threats and financial motives are related to patent purchases. However, firms with more potential synergies (via intellectual capital or growth options) acquire more patents, on average, and these relationships are economically large. Specifically, across firms, a one standard deviation increase in intangible capital stock (K_{INT}) and patent stock are associated with increases in patent purchases of 59% and 25%, respectively.[42] Moreover, one standard de-

[40] A relationship between constraints and the amount of patent purchases is unlikely because licensing can be used to facilitate sales to constrained buyers. Indeed, I show in the next section and Eisfeldt and Rampini (2009) shows in a lease vs. buy setting for equipment purchases, more financially constrained firms are able to use licenses and leases acquire the use of assets despite contraints. Thus, more constrained firms can shift the contractual method of acquisition instead of reducing acquisitions.

[41] See Dischinger and Riedel (2011), Karkinsky and Riedel (2012), and Sikka and Willmott (2010).

[42] The marginal effects of the coefficients are given by $exp(.464) - 1 = 0.59$ and $exp(.221) - 1 = 0.25$.

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viation increases in *Total Q* and sales growth are associated with 4% and 3.3% increases in acquisition activity.

Controlling for amount of intellectual capital with those two stock variables, firms with higher R&D ratios buy fewer patents. This relationship is driven by firms whose lower R&D to lagged asset ratio is due to having more assets, however, and not due to more R&D per se. In unreported tests, I directly add firm size to the estimation or interact firm size with R&D and find that larger firms acquire more and the relationship with R&D intensity disappears.[43]

Column 2 assess the drivers of patent divestitures and broadly finds support for each set of hypothesized forces. More intellectual capital is related with increased selling (as it is with buying), and again, these relationships are economically large. A one standard deviation increase in intangible capital stock (K_{INT}) and patent stock are associated with increases in patent sales of 60% and 47%, respectively.[44] Firms with higher R&D ratios sell fewer patents controlling for amount of intellectual capital. As with column 1, I directly add firm size to the estimation in unreported tests and find other coefficients unaffected. However, in contrast to the firm size test for patent acquisitions, size is unrelated to selling, conditional on the other controls. Multicollinearity issues complicate interpretation of this, but it is worth noting that the negative relationship between R&D ratio and selling remains significant.

While sellers tend to have more intellectual capital to sell, they tend to have deteriorating sales and innovation trajectories. A one standard deviation *decrease* in sales growth and patent growth is associated with increased patent sales of 3% (t=-3.1) and 2% (t=-1.9), respectively. This suggests that patent sales transfer patents to firms more able to exploit the patents.[45]

Litigation risks and taxes are related to patent sales (though not purchasing). A one standard deviation increase in litigation by technology peers is related to 7% fewer patent sales. Increasing tax rates by one standard deviation is related to an 11% reduction in sales, consistent with firms holding on to assets that can reduce taxes. This latter result holds within firm as well (column 6): as a firm's marginal tax rate increases, it becomes less likely

[43] Asset size is not explicitly included in the baseline model because of high multicollinearity with intangible stock. Nevertheless, in the unreported specification, all other coefficients maintain their sign, magnitude, and significance. This check motivates and assures the removal of assets from the model and the primary interpretation of the intangible capital variable. (Intangible capital stock is related to firm size, yet its coefficient is little changed by including firm size.)

[44] The marginal effects of the coefficients are given by $exp(.475) - 1 = 0.6$ and $exp(.382) - 1 = 0.47$.

[45] Serrano (2011) estimates large gains from trade in the market for patents. He argues that this is consistent with patent trades reallocating patents to firms more effective at commercializing patents, building on them, or resolving patent disputes outside of courts (as in Galasso, Schankerman, and Serrano (2013)).

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to sell.

Column 3 reports that larger intellectual stocks, specifically patent stocks, make firms 16% (t-stat of 8.4) more likely to sell than to buy. Meanwhile, firms buy more on net as their growth prospects increase. A standard deviation increase in each of the three growth proxies—*Total Q*, *Sales Growth*, and *Patent Growth*—is related to about 5% more net patent purchases, with p-values for each coefficient below 1%. Finally, driven by reductions in selling, firms become net buyers as peer litigation and marginal tax rates increase.

Overall, the cross sectional evidence indicates that patent acquirers appear to have more potential synergies, in that they have more technical expertise and growth options. Acquisition activity is not related to competitive threats or industry patent litigation. The lack of a relationship between patent acquisitions and litigation might be due to seller factors; sellers in litigious industries substantially reduce patent sales. Patent sellers have more intellectual capital, as expected, but deteriorating performance in the product and technology markets.

C Within firm determinants of patent market activity

Columns 5-7 of Table VI repeat the estimations of columns 1-3 with the addition of firm fixed effects. Here, I focus on the coefficients whose significance differs from the cross sectional regression.

The largest departure of the within firm specifications is the finding on R&D. Importantly, I find no relationship between lagged R&D and patent acquisitions, sales, or net acquisitions. This implies that the main result (patent acquisitions are related to future R&D expenditures) is not driven by preexisting trends within the firm.

For patent acquisitions (column 5), following the addition of fixed firm characteristics, only intangible capital and sales growth remain statistically significant. This motivates a robustness test for the main results which controls for possible selection effect dues to within firm changes in intangible capital and sales growth that may also be correlated with R&D changes. This test is included in Table IA.2 and the main results are unchanged. The difference between the within firm and cross sectional estimates shows that firms with larger patent stocks and higher Q relative to peers buy more patents on average, but increases in patent stock and Q *within a firm* are not related to purchasing.

Meanwhile, other than the coefficient on R&D, the determinants of patent divestitures (column 6) remain largely the same after firm fixed effects are added.[46]

[46] The t-statistic on patent growth, 1.61, is marginally below the cutoff.

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D Patent acquisition vs. patent generation

Should we think of acquired patents simply as outsourced patents? Are the motives for patent creation different from buying a patent, and how? This question is related to a large literature in finance, strategy, and economics relating to the management of innovation and research strategies and to the make or buy literature in organizational economics.[47] These literatures describe how the organization of firms, including the organization of R&D programs, relates to how firms buy (principally via mergers), make, or ally with others to obtain innovation.

Column 4 of Table VI reports the determinants of patent generation in this sample. As is standard in the literature, I find that patent generation is statistically higher for firms with larger stocks of intellectual capital (proxied by K_{INT} and *PatStock*), firms with more growth opportunities, and firms whose technological area is more contested (proxied by *ProdMktFluidity* and *TechPeerLit*).[48]

Column 4, contrasted against column 1, highlights that, at a basic level, patent creation (column 4) is not driven by the same factors as patent acquisition (column 1). For example, increased technological risks (measured by *ProdMktFluidity* and *TechPeerLit*) are associated with more patents grants, but not more patent purchases. If firms typically respond to litigation and competitive risk by applying for and receiving more patents, why do they not also increase patent acquisitions? Purchasing certainly has advantages relative to applying for a new (but similar) patent; it is faster than the USPTO approval process, the value of a current patent is more certain than a prospective patent, and purchased patents can no longer be used by competitors. This question, in turn, brings up a larger point. The difference in the coefficients implies that either the costs and benefits of patent acquisition differ in important ways from patent creation (thus leading to economically rational differences in the point estimates) or, if patents are simply outsourced patents (and the coefficients "should" be equivalent), that market frictions such as search costs prevent firms from taking the desired purchasing actions. A full examination of this point is outside the scope of this paper, but interesting.

More important is an implication based on the estimates in column 3 and column 7 (net patent acquisitions). Currently, virtually all studies that use patent stock as a variable of interest measure it under the assumption that patents are not transferred, largely due to

[47] E.g., Acharya, Baghai, and Subramanian (2014), Arora, Belenzon, and Rios (2014), Hackbarth, Mathews, and Robinson (2014), Manso (2011), and Robinson (2008).

[48] See Ziedonis (2004), among others, on patenting in contested areas.

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the challenge of identifying the firms in a patent transaction; precisely the challenge this paper overcomes. Yet, approximately 20% of all patents are sold or licensed at some point. Moreover, in my sample, 9% of firm-years that buy a patent have no patent stock under the standard method of accounting for patents! At the firm level, 64% of firms buy or sell a patent. Thus, measurement error in patent stock is pervasive. The implication of column 3 is that this measurement error is not random noise. In principle, this means other variables in a regression (including this table in this paper) with patent stock could be biased in any direction if the residual is correlated with determinants of net patent purchasing.

That 20% of patents are traded during their lifetime prompts the measurement problem, but there is a cheap solution available to researchers to reduce the scope of the problem using standard patent data without explicitly accounting for all transactions. Figure I shows that about 10% of patents are transacted within the first four years (roughly about 2.5% a year), a number similar to those reported by Serrano (2010) using an earlier version of the dataset. This suggests that a patent stock measure based on recently received patents will have less measurement error. In unreported tests, I replace the patent stock measure with recent grants (e.g. grants received in the prior three or four years) and find similar results.

IV Contracting decisions in patent markets

Until this point, the focus has been on investment and innovation *after* a patent transaction and on the characteristics of firms *before* a patent transaction. This section analyzes the transaction itself to shed light on the contractual dynamics at play and the key considerations of the parties involved. Specifically, this section investigates the determinants of the type of the transaction contract—purchase or license. The distinction between these two contract types is important, as the choice essentially allocates ownership of the patent going forward; in a license, the patent is retained by the seller but used by the buyer. Thus, the contract sets firm boundaries, and this setting offers a novel way to understand the dynamics that contribute to organizational form.

The primary difference between purchase and license agreements, besides ownership, is that patent licenses often contain royalties. Royalties are typically a share of revenue or income.[49] Because royalties effectively transfer equity in products based on the patent from the buyer to the seller, licenses decrease the marginal product of investment for the buyer. Given

[49] Survey evidence suggests that approximately three quarters of license agreements include some form of royalty.

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the results of the previous sections—that buyer complementarities are related to acquisitions and acquisitions are related to future investment—and the investment distorting nature of royalties, it is natural to wonder how the contract type is related to buyer complementarities.

The richness of this (unexplored) contracting setting allows us to observe direct relationships between buyers and the assets involved based on on citation links. Preexisting citations reveal a type of complementarity, in that buyers citing a patent have existing research capacity directly related to the patent. Because the contractual form is the outcome of a negotiation between two parties, this section analyzes the complementarity/ownership relationship within a contracting framework. Section IV.B describes the baseline model, which is estimated in Section IV.C. Section IV.D adds a measure of buyer citations to the baseline model and estimates whether the contractual form of acquisition is related to buyer complementarities.

A Transaction level sample

Section II.B described the construction of a patent transaction level dataset with firm identifiers for buyers and sellers. Each transaction is a purchase or a license agreement. This dataset was used in prior sections to construct firm-year variables. In this section, I instead modify the dataset to focus on questions at the *transaction level* itself.

To highlight the forces relevant to the contract choice, I remove transactions with more than one assignor or more than one assignee. These are cross-licenses and bundled sales and including them will introduce many confounding legal and product market forces that drive large scale agreements outside the core focus of this section. Because firm information is required, I keep transactions where either side of deal is a public firm. I discuss these restrictions in more detail later. Additional details on the transaction sample are detailed in Appendix IA.A.

[Insert Table VII about here]

Table VII describes this transaction level dataset. Panel A tabulates the number of transactions and patents transfered and highlights the dominance of patent sales as a method of transfer; only 2% of transactions are licenses. Of the 215,972 transactions, 91,262 are between two public firms, 72,970 involve a public buyer, and the remaining 51,740 involve a public seller.

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Panel B highlights some differences between the patents involved in sales and licenses. On average, sales involve 0.8 more patents and sold patents are one year younger. These univariate differences are statistically significant. Patents involved in licenses are less cited on average but their grants were associated with larger market impacts. Sellers cite licensed patents 1% less frequently. Notably, technological links between the buyers and the patents are explicit and surprisingly frequent given the young age of patents: 25% of all transactions involve patents cited by the buyers before the transaction. These linkages provide an asset level validation of the notion that buyers enter the market to acquirer complementary assets.

B Theoretical discussion and empirical contracting model

The goal of this section is to construct an empirical model that can be estimated and then augmented with a new buyer complementarity factor. While the buy or license decision is an under explored empirical setting, much theoretical literature exists to guide the selection of factors for a baseline contracting model. The question of ownership has antecedents in studies of vertical integration[50] and buy or lease decisions.[51] Both strands of literature start with the assumption that the contracting parties endogenously choose the contract which maximizes overall surplus (subject to individual constraints) and then bargain over the surplus by setting contract terms. The literatures differ somewhat in the contracting factors that receive attention, however, and in this study, the baseline model includes the union of key factors. The vertical integration literature highlights the role of patent productivity, transaction costs, and bargaining power. The financing literature highlights the role of tax differentials and buyer financing constraints.

To capture that richness and analyze what factors drive the license versus sale decision, the baseline specification focuses on cross-sectional variation within a technology area–year. To allow flexible fixed effects, I specify the following linear probability model on the transaction-

[50] E.g. Grossman and Hart (1986), Aghion and Tirole (1994), and Hart and Moore (1990).
[51] E.g. Eisfeldt and Rampini (2009), Sharpe and Nguyen (1995), and Rauh and Sufi (2012).

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level sample

$$\begin{aligned}\text{License}_{c,b,s,p,t} =& \beta_1 \times \text{Patent value}_{p,t} \\ &+\beta_2 \times \text{Tax differential (seller-buyer)}_{b,s,t} \\ &+\beta_3 \times \text{Buyer financial constraints}_{b,t} \\ &+\beta_4 \times \text{Relative licensing transaction costs}_{c} \\ &+\beta_5 \times \text{Bargaining power}_{b,s,t} + \alpha_{p,t} + u_{c,b,s,p,t} \end{aligned} \tag{4}$$

where c is a contract that transfers some patents p between a buyer b and seller s in year t. Technology area-year fixed effects $\alpha_{p,t}$ absorb variation due to technology specific time trends.[52] To the extent that industries cluster by technology area of patent classification, this specification also absorbs time-varying industry forces.[53] Standard errors are heteroskedastic robust. The appendix describes the construction of the contract level sample.

Because the sample includes private-to-public and public-to-private transactions (in addition to public-to-public), buyer and seller variables (including potential industry fixed effects, firm fixed effects, and firm based clustering) will not have full coverage. I adopt the convention of setting missing values of variables to zero and including dummy variables equal to one if missing to absorb the variation in these observations. As a check of possible collinearity issues induced by this procedure, I examine variance inflation factors and find that they are below standard thresholds across all specifications. Additionally, I perform robustness tests (unreported, but available from the author) on subsamples that do not have missing information and find similar results. These robustness tests address concerns with both the missing variable procedure and possible bias induced by including private firms (which might include patent trolls).

One final issue is the nature of license agreements in the sample. Non-exclusive licenses have substantively different contracting dynamics, and their impact on the coefficient estimates and the appropriate interpretation is unclear. The imposed sample restriction keeping transactions with only one assignor and one assignee deals with this challenge in part by ruling out obvious cross-licenses and bundled sales. This restriction is conservative, in that

[52] Technology class based on the CPC standard used by the USPTO, and there are more than 470 classes. This choice—using technology class instead of industries—has the advantage of being fully defined across observations; nevertheless, I run industry (buyer, or separately, seller) × year fixed effects in unreported robustness tests and find similar results. For transactions with multiple patents, I pick the classification of the most cited patent.

[53] In robustness tests, I directly include buyer industry × year fixed effects and find similar results. Using seller industry instead also yields similar results.

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some patents might be licensed non-exclusively at different times and remain in the base sample. In unreported tests, I make an aggressive assumption that rules out any transactions whose patents were licensed out by the same party multiple times within five years. This restriction is aggressive, in that some patents might be licensed for short terms. Conclusions remain unchanged.

Next, I discuss the received economic and empirical theory for how each of the baseline variables relate to the likelihood of using a license contract. The first two factors, patent value and tax differential, have theoretically ambiguous predictions. Thus, their average relationship with the contract type is an empirical question with an unknown answer. The latter three factors have unambiguous predictions and testing them empirically provides a sensibility check for this setting.

B.1 Patent value and contracting

The impact of patent value on contractual form is theoretically ambiguous for the following reasons. Royalties induce investment distortions because they function as a tax on production and investment. Thus under a license contract, the buyer will invest less than they would under a sale agreement (wherein the buyer has full equity and perfectly aligned incentives). Aghion and Tirole (1994) show that this underinvestment increases as the value of the patent increases. The tradeoff is that, for any given level of investment, more valuable patents will generate more licensing income.

Thus, β_3 will be positive (more valuable patents are more likely to be licensed) if the licensing revenue effect dominates the investment distortions and negative if investment distortions dominate. Empirically, I proxy for ex-ante patent value with two variables.[54] The first, *Patent XRET*, is the excess stock return of the firm that receives the initial grant on the day of the patent's announced grant (following Kogan, Papanikolaou, Seru, and Stoffman (2012)). The second, *Previous Cites*, is based on citations and measured as the logged number of preexisting citations for patents in the deal.[55]

B.2 Taxes

The classic implication of tax differentials between the buyer and seller in a buy or lease setting is to allocate the asset to the high tax party. This maximizes tax savings, which the parties then bargain over. However, the lessons of those studies need not apply directly to

[54] Including them separately or together does not alter any conclusions.
[55] For both of these measures, I choose the maximum across the patents in the deal.

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patent ownership because licensing royalties shift the legal incidence of income. This gives the parties the ability to increase tax savings by shifting income to the *low* tax party.

Consider an example where the seller's marginal income is taxed at 10% while the buyer's marginal income is taxed at 30%. In a lease setting, allocating the asset to the buyer via a sale rather than in a lease means that the tax shields generated by the asset are three times larger. Such tax shields would predict that β_2 is positive: when the seller has higher (lower) taxes, the contract should be a lease (sale), so that the high tax seller (buyer) produces the maximum tax shields.

The picture changes if instead the same parties were considering transferring a patent that was expected to generate $1M a year in taxable income. Suppose the licensing royalty rate is exogenously set at 50% and based on income. Then, in choosing between a license and a purchase agreement, the parties essentially choose who realizes $500,000 in profits. By selecting a license, the parties reduce the taxes by $100,000 annually. This royalty effect would instead predict that β_2 is negative.

Because patents are depreciable, it is reasonable to expect both effects—tax shields and income shifting—to be present in the data. Therefore, a significant relationship between the tax differential of the parties implies that one effect dominates the other. I measure *Tax differential (Seller-Buyer)* using data based on the procedure in Blouin, Core, and Guay (2010).[56]

B.3 Financial constraints

Eisfeldt and Rampini (2009) finds that more constrained buyers prefer to lease because leases allow the seller to, in effect, extend a type of financing due to the differential bankruptcy treatment of owned and leased property. As the institutional rules that drive their finding also apply to licensing, I expect that constrained buyers, measured with the *Buyer DelayCon* variable, are more likely to enter into a license than a sale agreement ($\beta_3 > 0$).

In a second test, I decompose financial constraints into equity constraints (*Buyer Eqty DelayCon*) and debt constraints (*Buyer Debt DelayCon*). Hoberg and Maksimovic (2015) report that firms facing equity constraints have "material undisclosed proprietary informa-

[56] In robustness tests, I also measure the differential with rates from Graham (1996). Additionally, for both sets of tax measures, I decompose the differential into the seller and buyer rate. The conclusions are consistent, as seller tax rates have a positive relationship with licensing and buyer tax rates have a negative relationship with licensing. Robustness to this procedure is important because while *Tax differential (Seller-Buyer)* is a direct measure, it only uses variation in the public to public subsample. The decomposed tests are less direct measure, but use variation across more observations. For example, seller tax rates is defined for the public to public *and* public to private subsamples.

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tion" and are constrained from funding growth opportunities. If the finding of Eisfeldt and Rampini (2009) applies to patent contracts, equity constraints are precisely the type of constraint that would spur a firm to use licensing. I thus hypothesize that any relationship between constraints and licensing is concentrated among firms facing equity constraints.

B.4 Transaction costs

Relative to a sale agreement, licenses mandate monitoring costs by the seller to ensure appropriate payment, prevent infringement, stop invalid sublicensing, and ensure licensees do not sidestep the agreement by acquiring new patents that displace the seller's. As monitoring costs increase, overall surplus of licensing decreases relative to sales, and licensing becomes less likely. These costs should increase as the number of patents in a deal increases, so I proxy for *Relative licensing transaction costs* with the logged number of patents in the transaction (*Patents in Deal*), and expect a negative estimate for β_4.

B.5 Bargaining power

In contracting models, contract form is typically set by the surplus and then bargaining power either sets terms of the negotiation or price terms. However, firms may have preferences over control of the patent that impact their perceived surplus from a proposed deal. Patent transactions are one such setting where that preference is likely to occur, because patents have increasing returns to scale properties in that average patent values increase with the number of patents in a pool. There are several reasons for this, including library licensing and litigation "war chests." This reasoning implies that firms likely assign value to controlling the patent rights. War chests have value because they affect litigation (firms can tie up opposing parties in more litigation, for example) and it is likely that litigation war chests can be used in negotiations over patent transactions. I thus account for bargaining power of each party with their measured patent stock and hypothesize that licensing is likely when a buyer has more patents and more likely when a seller has more patents.[57]

C Empirical determinants of licensing vs. selling

Table VIII reports the estimates of Equation 4. To ease interpretation, all continuous independent variables are standardized. The dependent variable is scaled by 100, so continuous coefficients should be interpreted as percentage point changes for a one standard deviation

[57] *Buyer PatStock* and *Seller PatStock* are each citation weighted and in log form.

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change in that independent variable. The economic magnitude of coefficients can be judged relative to the unconditional licensing propensity of 2.1%.

[Insert Table VIII about here]

Column 1 estimates the base model, which unanimously supports the unambiguous predictions, both statistically and economically. I find statistically significant evidence that licensing is decreasing in the number of patents in a deal, which proxies for relative transaction cost of licensing (-0.20 percentage points (p.p.), t-stat of 4.7), and *Buyer PatStock*, which proxies for buyer bargaining power (-0.09 p.p., t-stat of 1.8).[58] *Seller PatStock*, which proxies for seller bargaining power, is significantly and positively related to the use of licensing (0.28 p.p., t-stat of 4.0), as is buyer financial constraints (.23 p.p., t-stat of 3.8). The finding on buyer constraints extends the buy or lease findings of Eisfeldt and Rampini (2009) to patent licensing. Decomposing the constraints into equity and debt components in column 2, I find an even stronger association with licensing as firms become more equity constrained, as expected. A one standard deviation increase in equity constraints is related 0.33 p.p. more licensing, which is 16% of the sample mean licensing rate.

The two sets of variables that have theoretically ambiguous predictions—tax differentials and patent value—have statistically significant coefficients empirically. Consistently, I find that more valuable patents are licensed more often and thus remain the property of their sellers. In fact, both *Patent XRET* and *Previous Cites* are highly significant across all models and in unreported tests where they are included separately. The estimates are robust to separately including seller citations to the patents in the deal.[59] Moreover, the estimates are economically large. A one standard deviation increase in XRET and logged citations is associated with license propensity increases equivalent to 16% and 8% of the sample mean licensing rate. The positive relationship between patent value and licensing indicates that, on average, as transaction patents become more valuable, the increase in licensing income outpaces the value loss due to underinvestment.

Empirically, tax differentials also turn out to be a powerful predictor of the contract form. As the tax rate of sellers increase and buyers decrease (i.e. *Tax Differential (Seller-Buyer)*

[58] "p.p" means percentage points.

[59] This would matter if *Previous Cites* was loading on citations from sellers. In this case, the interpretation would be that sellers keep patents in which they have conducted follow on research. These patents might be considered core patents sellers have large financial interests in maintaining. The coefficient on *Seller Cites* is significant and positive.

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increases), transactions are more likely to be a sale. Specifically, a one standard deviation increase in the seller's relative marginal tax rate is associated with a 0.56 p.p. (t-stat of 6.96) decrease in the likelihood of a license. This is the largest coefficient in magnitude, equivalent to 27% of the sample mean rate of licensing. This result is robust to decomposing the tax coefficient into separate buyer and seller components or using the tax measure from Graham (1996). Thus, in the data, ongoing revenue tax considerations dominate depreciation tax shields on average. This squares with recent evidence from press articles and SEC disclosures that licensing revenues can be substantial.[60]

D Acquirer-patent complementarities

Conceptually, acquirer complementarities with patents represent a form of acquirer specific value. Thus, the expectation is that relationship between buyer complementarities and contract type matches that of the common value measures. Hence, a positive relationship is expected.

Columns 3 and 4 of Table VIII test this hypothesis. I create two direct measures of acquirer-patent complementarities revealed by citations. In column 3, I include *Log(1+Buyer Cites)*, which counts the number of times the acquirer cited the patent before the transaction. In column 4, I include *Frac. Cites from Buyer*, which is the number of times the acquirer cited the patent divided by overall citations it received. These two variables capture different dimensions of acquirer complementarities. The former indicates the extent to which the buyer has preexisting related research. The latter indicates how specific the asset is to the buyer.

As predicted, both enter positively and significantly; higher acquirer-patent complementarities is associated with a higher likelihood of a license agreement. The coefficients are of the same magnitude as financial constraints. The positive relationship support the interpretation of these complementarities as a buyer specific version of value.

Column 5 asks whether this relationship is related to product market competition. To the extent that buyers that place a higher valuation on patents, fully aligned incentives (and thus purchasing) becomes more important. Indeed, column 5 reports that this is the case when firms are not competitors.

[60] IBM and TI were the first firms to break $1 billion in annual royalty revenue. Recently, Qualcomm has generated revenue in excess of $6 billion, while Microsoft and Ericsson earned more than $2 billion a year.

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V Conclusion

The main message of this paper is that transactions in the secondary patent market are important to understand, with implications for investment policy, patent design, and organizational economics. Over the last three decades, the secondary patent market has grown rapidly to become a pervasive part of the life of a patent and the innovation management of firms. At the same time, the changing nature of the economy, in which more firms can scale production and deliver electronically at near zero cost, makes the reallocation of ideas and patents especially powerful.[61]

These trends make it crucial to advance our understanding of transactions in the market for patents and markets for other forms of intellectual property. This paper takes a step in that direction by linking patent transactions to information on firm investment. At the same time, my findings and conclusions bring up new questions for future research that I plan to explore. First, this paper focuses on patent transactions in isolation. Yet, firms have a menu of contract options that bring new and innovative projects into the firm, including mergers, strategic alliances, and corporate venture capital.[62] How do patent acquisitions fit into the set of options available and what tradeoffs dominate the choice? Second, I highlight the widespread use of patent markets by public firms and corroborate the large fraction of patents that are traded first documented by Serrano (2011). The unexplored implication of the large fraction of patents that are traded is that patent stocks, as measured in the literature, rely on a false assumption: patents granted to a firm stay with the firm until expiration. Exploring this assumption offers a promising avenue to clarify existing puzzles in the literatures on innovation and investment. Finally, linking patent transactions to firm identifiers makes new research on peer-to-peer technology relations, competition, cooperation, and investment possible.

[61] Consider the recent example of Niantic, the maker of the game Pokemon Go. Within a year of spinning out of Google in the fall of 2015: (1) Niantic licensed the use of Pokemon characters from Nintendo; (2) Launched a product—a game for smartphones—globally; and (3) Earned approximately $16 million in sales based on 40 million daily customers in the first month of release. This rapid success was facilitated by the pivotal license with Nintendo.

[62] E.g. Arora, Belenzon, and Rios (2014), Hackbarth, Mathews, and Robinson (2014), Ma (2015), and Robinson (2008).

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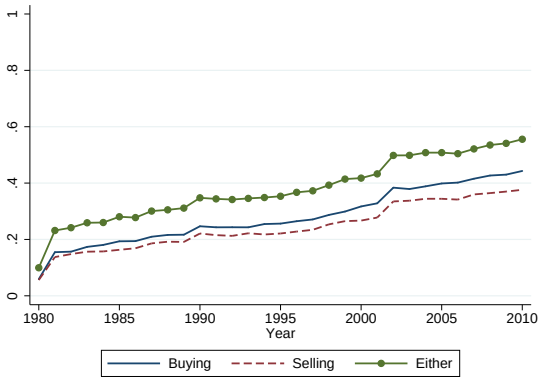
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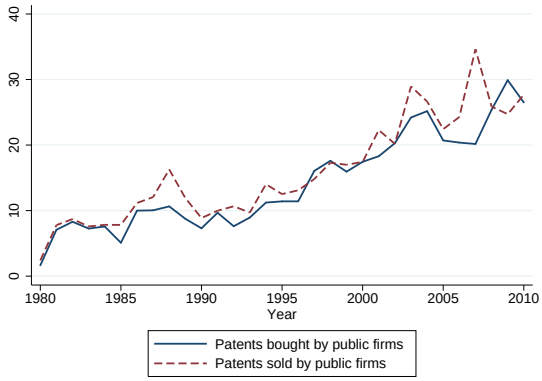
Figure I: Patent market size

This figure depicts widespread participation in the patent markets. The sample for Panels A and B comprises all Compustat firm-years between 1980 and 2010. I exclude firms in SIC 49, 6, and 9 and firms whose cash flow identity does not hold (see Chang, Dasgupta, Wong, and Yao (2014)). Panel A reports the annual fraction of public firms that buy or sell patents. Panel B reports the total transaction volume, in terms of the number of patents involved, among public firms. The sample for Panel C comprises all US utility patent grants from 1980-2010. For each patent cohort, Panel C reports the fraction of patents that are transacted by 2014 in the solid line and the fraction that are transacted within four years of being granted in the dotted line.

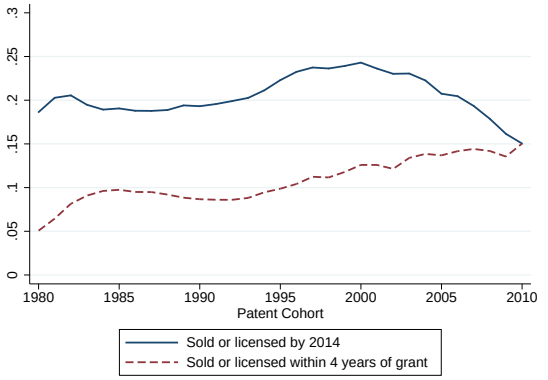
Panel A: Fraction of public firms using patent market



Panel B: Volume of public firm patent market (000s)



Panel C: Fraction of patents sold or licensed, by year of patent grant



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Table I: Fraction of Compustat values in patent transaction years

This table reports widespread participation in the patent markets. The sample comprises all Compustat firm-years between 1980 and 2010. I exclude firms in SIC 49, 6, and 9 and firms whose cash flow identity does not hold (see Chang, Dasgupta, Wong, and Yao (2014)). The firm-life level counts the fraction of public firms that buy patent rights (Column 1), sell patent rights (Column 2), or do either (Column 3) at any point in the sample. Patent right transfers include sale and license agreements. The firm-year level statistics report the fraction of total Compustat values for a given variable that are accounted for by firm-years where the firm buys, sells, or does either. Assets (Compustat variable AT), profits (OIBDP), and R&D (XRD) are inflation adjusted to 2009 values using the GDPDEF series posted on the BLS website.

	Buyer	Seller	Either
Firm-life level:			
Firms	56.0	51.1	63.8
Firm-year level:			
Firm-Years	27.9	24.3	37.7
Assets	58.2	55.1	67.9
Profits	58.5	55.1	68.0
Patent Grants	85.9	82.2	91.6
R&D Expenses	81.4	76.6	87.5

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Table II: Summary statistics of firm-year regression sample

This table provides summary statistics for the firm-year sample. The sample comprises Compustat firm-years between 1976 and 2014 with active R&D programs and sufficient data on the control variables. I exclude firms in SIC 49, 6, and 9 and firms whose cash flow identity does not hold (see Chang, Dasgupta, Wong, and Yao (2014)). Data on patent grants come from Kogan, Papanikolaou, Seru, and Stoffman (2012), citations data from Google Patent Grants, and patent transactions from the USPTO Patent Assignment Dataset. Construction of the sample is described in detail in the Internet Appendix. *R&D, CAPX, Advertising,* and *AT* are Compustat variables XRD, CAPX, XAD, and AT, respectively. *Grants* is the flow of patent grants a firm receives. *Cites* is the flow of citations received by internally granted patents. *Originality* captures the breadth of technologies upon which the new patent grants of a firm rely. A value of 0 means the firms patents only cite one technology field, while a value of 1 means they equally cite all technology fields. *PatAcq (CW)* and *PatDiv (CW)* are the flow of patents acquired and divested, citation weighted on the day before the transaction. *NewPatStock* is new citation weighted patent stock (*Grants* + *Cites*). *Total Q* is from Peters and Taylor (2016). *Cash Flow* is cash flow over assets as defined as in Chang, Dasgupta, Wong, and Yao (2014). The variables defined as ratios (*R&D/AT, CAPX/AT, Advertising/AT, Total Q,* and *Cash Flow*) are winsorized at the 1% level annually.

	N	Mean	SD	P10	P50	P90
Dependent variables:						
$R\&D_t/AT_{t-1}$	53,745	0.11	0.15	0.01	0.06	0.25
$CAPX_t/AT_{t-1}$	53,745	0.06	0.07	0.01	0.04	0.13
$Advertising_t/AT_{t-1}$	53,745	0.01	0.04	0.00	0.00	0.03
$Log(1+Grants)_t$	53,745	1.21	1.51	0.00	0.69	3.43
$Log(1+Cites)_t$	53,745	2.18	2.23	0.00	1.61	5.44
$Originality_t$	53,745	0.31	0.31	0.00	0.30	0.73
Independent variables:						
$Log(1+PatAcq\ (CW))_{t-1}$	53,745	0.85	1.50	0.00	0.00	3.22
$Log(1+PatDiv\ (CW))_{t-1}$	53,745	0.79	1.51	0.00	0.00	3.14
$Log(1+NewPatStock)_{t-1}$	53,745	2.11	2.24	0.00	1.61	5.41
Total Q_{t-1}	53,745	1.64	4.03	-0.01	0.65	3.72
Cash $Flow_{t-1}$	53,745	0.01	0.23	-0.24	0.07	0.18
$Log(Assets)_{t-1}$	53,745	5.22	2.31	2.45	4.93	8.42

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Table III: Predicted relationships with patent acquisitions at time t

This table summarizes the predictions of Section II.C for Table IV and Table V. The first two columns relate the predictions if patent acquisitions complement future R&D and the last two columns cover the case where patent acquisitions substitute for future R&D.

Case:	If patent acquisitions and R&D are complements		If patent acquisitions and R&D are substitutes	
Time period:	At $t+1$	At $[t+2, t+4]$	At $t+1$	At $[t+2, t+4]$
Coefficients:	$\alpha_{1,1}$	$\{\alpha_{1,2}, \alpha_{1,3}, \alpha_{1,4}\}$	$\alpha_{1,1}$	$\{\alpha_{1,2}, \alpha_{1,3}, \alpha_{1,4}\}$
Investment types:				
R&D	+	+	−	−
CAPX	0/−	+	+	+
Advertising	0/−	+	+	+
Flow of internal innovation:				
Grants	0/+	+	0/−	−
Cites	0/+	+	0/−	−
Originality	0/+	+	0/−	0/−

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Table IV: Patent acquisitions, investment, and innovation

This table reports the relationship between patent acquisitions and future investment and internal innovation output. Analysis is based on an OLS estimation of Equation 1. The firm-year sample and variable definitions are described in Table II. The dependent variables in the first three columns (under *Investment Ratios*) are normalized by lagged assets and multiplied by 100, so coefficients for those models should be interpreted in terms of percentage points. To facilitate interpretation, *Total Q, Cash Flows,* and *Log(Assets)* are standardized. Industry by year fixed effects absorb industry specific time trends, and firm fixed effects are included. T-statistics are reported in parentheses. Standard errors are clustered by firm. The symbols ***, **, and *, indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Investment Ratios (×100)			Internal Innovation (Flow variables)		
	R&D	CAPX	Advertising	Log(1+Grants)	Log(1+Cites)	Originality
Log(1+PatAcq (CW))$_{t-1}$	0.079***	0.026	-0.009	0.028***	-0.003	0.003***
	(2.69)	(1.39)	(-1.13)	(8.01)	(-1.19)	(3.31)
Log(1+PatDiv (CW))$_{t-1}$	-0.105***	-0.085***	0.015*	-0.003	-0.002	-0.001
	(-3.42)	(-4.27)	(1.84)	(-0.71)	(-0.73)	(-1.32)
Log(1+NewPatStock)$_{t-1}$	0.134**	-0.183***	0.024	0.249***	0.740***	0.012***
	(2.02)	(-4.59)	(1.17)	(25.35)	(116.12)	(8.09)
Total Q$_{t-1}$	0.445***	0.780***	0.104***	-0.013***	-0.032***	-0.007***
	(4.64)	(12.22)	(3.79)	(-3.24)	(-10.01)	(-4.84)
Cash Flow$_{t-1}$	-2.798***	0.369***	-0.005	-0.041***	-0.012***	-0.003
	(-19.28)	(5.91)	(-0.18)	(-7.08)	(-2.72)	(-1.35)
Log(Assets)$_{t-1}$	-9.884***	-3.569***	-0.626***	0.483***	0.199***	0.082***
	(-25.29)	(-17.93)	(-6.82)	(18.49)	(13.15)	(12.21)
Year × SIC3 FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	51,983	51,983	51,983	51,983	51,983	51,983
Adj. R^2	0.74	0.40	0.74	0.81	0.93	0.41

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Table V: The dynamic relationship between patent acquisitions, investment, and innovation

This table reports the dynamic relationship between patent acquisitions and future investment and internal innovation output. Analysis is based on an OLS estimation of Equation 2. The firm-year sample and variable definitions are described in Table II. The dependent variables in the first three columns (under *Investment Ratios*) are normalized by lagged assets and multiplied by 100, so coefficients for those models should be interpreted in terms of percentage points. Firm-year level controls *NewPatStock, Total Q, Cash Flows,* and *Log(Assets)* are not reported for brevity. Industry by year fixed effects absorb industry specific time trends, and firm fixed effects are included. T-statistics are reported in parentheses. Standard errors are clustered by firm. The symbols ***, **, and *, indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Investment Ratios (×100)			Internal Innovation (Flow variables)		
	R&D	CAPX	Advertising	Log(1+Grants)	Log(1+Cites)	Originality
Log(1+PatAcq (CW))$(t-1)$	0.071**	0.011	-0.010	0.026***	-0.002	0.003***
	(2.44)	(0.60)	(-1.26)	(7.32)	(-0.73)	(3.25)
$(t-2)$	0.004	0.028	0.003	0.021***	0.003	0.002
	(0.14)	(1.48)	(0.32)	(5.75)	(0.88)	(1.58)
$(t-3)$	0.088***	0.042**	-0.001	0.017***	0.006*	0.001
	(2.94)	(2.15)	(-0.11)	(4.87)	(1.91)	(1.38)
$(t-4)$	0.036	0.043**	0.008	0.015***	0.002	0.001
	(1.09)	(1.97)	(0.99)	(3.88)	(0.74)	(0.83)
Log(1+PatDiv (CW))$(t-1)$	-0.101***	-0.091***	0.005	-0.004	0.001	-0.001
	(-3.41)	(-4.79)	(0.70)	(-1.15)	(0.44)	(-0.59)
$(t-2)$	-0.022	-0.040**	0.010	-0.008**	-0.002	-0.001
	(-0.74)	(-2.11)	(1.32)	(-2.25)	(-0.54)	(-1.42)
$(t-3)$	-0.061**	-0.050***	0.007	-0.015***	-0.011***	-0.002*
	(-2.07)	(-2.66)	(0.91)	(-3.77)	(-3.62)	(-1.82)
$(t-4)$	-0.003	-0.036*	0.004	-0.019***	-0.011***	-0.003**
	(-0.08)	(-1.81)	(0.44)	(-4.78)	(-3.32)	(-2.48)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year × SIC3 FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	40,159	40,159	40,159	40,159	40,159	40,159
Adj. R^2	0.75	0.43	0.77	0.83	0.93	0.43

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Table VI: Determinants of patent market activities

This table presents the OLS estimates on the firm-year sample described in Table II of Equation 3

$$y_{i,j,t} = \beta_1 \times \text{Internal Innovation}_{i,t-1} + \beta_2 \times \text{Competition and Litigation}_{i,t-1} + \beta_3 \times \text{Growth Opportunities}_{i,t-1} + \beta_4 \times \text{Financial Factors}_{i,t-1} + \eta_{j,t} + u_{i,j,t}$$

where $y_{i,j,t}$ is a flow measure of patent market activities or internal patent grants. Patent acquisitions (*PatAcq*) is defined as Log(1+PatAcq (CW)). Patent divestitures (*PatDiv*) is defined as Log(1+PatDiv (CW)). Net patent acquisitions (*NetAcq*) is defined as PatAcq minus PatDiv. Internal patent grants (*Grants*) is defined as Log(1+Flow Grants). *Internal Innovation* includes the stock of intangible capital (K_{INT}), the stock of patents (*PatStock (CW)*), and the R&D ratio. *Competition and Litigation* includes product market fluidity (*ProdMktFluid*) and a measure of litigation among technology peers (*TechPeerLit*). *Growth Opportunities* includes *Total Q, Sales Growth*, and *Patent Growth*. *Financial Factors* includes a measure of financial constraints (*Delaycon*) and the marginal tax rate (*MTR-BCG*). Variables are defined formally in Appendix A. To facilitate interpretation, all independent variables are standardized. Industry by year fixed effects ($\eta_{j,t}$) absorb industry specific time trends. T-statistics are reported in parentheses. Standard errors are clustered by firm. The symbols ***, **, and *, indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Cross sectional				Firm fixed effects			
	PatAcq (1)	PatDiv (2)	NetAcq (3)	Grants (4)	PatAcq (5)	PatDiv (6)	NetAcq (7)	Grants (8)
Log(1+K_{INT})$_{t-1}$	0.464***	0.475***	-0.011	0.534***	0.385***	0.193***	0.192***	0.656***
	(17.37)	(17.50)	(-0.58)	(23.13)	(6.25)	(2.71)	(3.36)	(15.93)
Log(1+PatStock (CW))$_{t-1}$	0.221***	0.382***	-0.161***	0.723***	0.055	0.126***	-0.071**	0.386***
	(8.59)	(14.05)	(-8.41)	(31.46)	(1.52)	(3.47)	(-2.12)	(12.60)
R&D$_{t-1}$	-0.031**	-0.039***	0.008	0.061***	-0.008	-0.012	0.004	0.015**
	(-2.11)	(-2.81)	(0.66)	(6.10)	(-0.58)	(-0.86)	(0.23)	(1.96)
ProdMktFluidity$_{t-1}$	0.007	-0.027	0.035	0.070***	0.036	0.045	-0.008	0.017
	(0.27)	(-0.99)	(1.61)	(3.84)	(1.38)	(1.52)	(-0.30)	(1.05)
Log(1+TechPeerLit)$_{t-1}$	-0.019	-0.071***	0.052***	0.204***	-0.034	-0.092***	0.057**	0.200***
	(-0.95)	(-3.30)	(3.17)	(14.06)	(-1.31)	(-3.28)	(2.11)	(15.00)
Total Q$_{t-1}$	0.040***	-0.004	0.043***	0.059***	0.016	0.003	0.012	0.020**
	(2.64)	(-0.27)	(3.59)	(4.83)	(1.10)	(0.27)	(0.81)	(2.32)
Sales Growth$_{t-1}$	0.033***	-0.028***	0.061***	0.011**	0.020**	-0.029***	0.049***	-0.005
	(3.52)	(-3.12)	(5.66)	(2.24)	(2.17)	(-3.25)	(4.25)	(-1.25)
Patent Growth$_{t-1}$	0.011	-0.019*	0.031***	0.326***	-0.000	-0.015	0.015	0.264***
	(1.12)	(-1.93)	(2.80)	(38.18)	(-0.05)	(-1.61)	(1.32)	(31.55)
Delaycon$_{t-1}$	-0.013	-0.021	0.008	0.040***	0.025	0.009	0.016	0.017*
	(-0.64)	(-1.02)	(0.49)	(3.20)	(1.35)	(0.45)	(0.79)	(1.72)
MTR-BCG$_{t-1}$	-0.016	-0.113***	0.097***	-0.027**	0.010	-0.072***	0.082***	-0.003
	(-0.93)	(-6.65)	(6.45)	(-2.16)	(0.58)	(-3.84)	(3.99)	(-0.29)
Year × SIC3 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE					Yes	Yes	Yes	Yes
Observations	40,394	40,394	40,394	42,411	40,106	40,106	40,106	42,011
Adj. R^2	0.17	0.21	0.01	0.71	0.33	0.35	0.05	0.84

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Table VII: Transaction level sample

This table presents summary statistics for the transaction level dataset, where either the buyer or seller is a public firm. The sample contains patent purchases and licenses over 1980-2014. I restrict the sample to deals with only one assignor and one assignee deals to rule out obvious cross-licenses and bundled sales. Construction of the dataset is described in Section IV.A and Appendix IA.A. Panel A tabulates the number of transactions based on whether the buyer and/or seller are publicly listed firms. Panel B reports the average of different transaction-level statistics separately for purchases and licenses, the difference of the means, and t-tests for difference of the means. The symbols ***,**, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. *Patents in Deal* is the number of patents in the transaction. *Patent Age* is the average age of the patents in the transaction. *Log(1+Previous Cites)* is the total number of preexisting citations received by patents in the transaction. *Patent XRET* is the maximum (across the patents in the deal) grant day excess return for the firm granted the patent. *Any Previous Cites by Buyer* and *Any Previous Cites by Seller* are equal to one if any of the patents in the deal were previously cited by the buyer and seller, respectively. Variables are defined formally in Appendix A.

Panel A: Frequency of transactions by public status of firms

	Purchase	License
Public to Public	89,297	1,965
Private to Public	71,578	1,392
Public to Private	50,805	935
Total	211,680	4,292

Panel B: Transaction level statistics

	Purchase	License	Difference	T-Stat
Patents in Deal	4.19	3.39	-0.80***	3.5
Patent Age	3.86	2.81	-1.05***	13.4
Log(1+Previous Cites)	0.99	0.94	-0.04*	1.9
Patent XRET	0.01	0.02	0.01**	3.6
Any Previous Cites by Buyer	0.25	0.25	0.00	0.1
Any Previous Cites by Seller	0.26	0.25	-0.01**	2.2

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Table VIII: Determinants of licensing

This table presents the estimates of a linear probability model of Equation 4,

$$\begin{aligned}\text{License} = \alpha_{FE} &+ \beta_1 \times \text{Patent value} + \beta_2 \times \text{Tax differential (seller-buyer)} \\ &+ \beta_3 \times \text{Buyer financial constraints} + \beta_4 \times \text{Relative licensing transaction costs} \\ &+ \beta_5 \times \text{Bargaining power} + u\end{aligned}$$

where the unit of observation is a patent transaction. The dependent variable is 100 if the contract is a license and 0 if it is a purchase, meaning that all coefficients should be interpreted in percentage point terms. The sample is a contract level database containing patent purchases and licenses over 1980-2014. Construction of the dataset is described in Section IV.A and Appendix IA.A. *Patent value* is measured based on information from the stock market (*Patent XRET*) and citations (*Previous Cites*). *Tax differential (seller-buyer)* is measured using data from Blouin, Core, and Guay (2010). *Buyer financial constraints* is measured using *Buyer DelayCon*. Column 2 decomposes constraints into equity and debt components. *Relative licensing transaction costs* is measured with *Patents in Deal*. *Bargaining Power* is measured with the stock of patents created by the buyer (*Buyer PatStock*) and the seller (*Seller PatStock*). Columns 3 to 5 include direct measures of buyer complementarity with acquired patents. *Buyer Cites* is the number of cites from the buyer to deal patents and *Frac. Cites from Buyer* is *Buyer Cites* divided by *Previous Cites*. Column 5 restricts attention to Public to Public deals. *Diff. SIC3* is an indicator equal to one if the buyer and seller were in a different SIC3. Variables are defined formally in Appendix A. To facilitate interpretation, all continuous independent variables are standardized. For each independent variable, missing values are set to zero and a dummy variable equal to one for these missing observations are included. The dummy variables are not included. Variance inflation tests are computed but not reported. Patent technology classification by year fixed effects ($\eta_{j,t}$) are included to absorb technology specific time trends. Heteroskedastic robust standard errors are reported in parentheses. The symbols ***,**, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

		Dependent variable: License, ×100				
	Predicted sign	(1)	(2)	(3)	(4)	(5)
Patent XRET	?	0.331***	0.330***	0.295***	0.299***	0.415***
		(3.40)	(3.40)	(3.03)	(3.07)	(2.63)
Log(1+Previous Cites)	?	0.163***	0.163***	0.382***	0.515***	-0.108
		(3.81)	(3.83)	(5.19)	(7.96)	(-1.48)
Tax Diff. (Seller-Buyer)	?	-0.562***	-0.585***	-0.570***	-0.574***	-0.205*
		(-6.97)	(-7.22)	(-7.07)	(-7.11)	(-1.89)
Buyer DelayCon	+	0.234***		0.228***	0.226***	0.321***
		(3.79)		(3.70)	(3.68)	(3.54)
Buyer Eqty DelayCon	+		0.327***			
			(5.05)			
Buyer Debt DelayCon	0		-0.059			
			(-0.92)			
Log(1+Patents in Deal)	-	-0.203***	-0.203***	-0.277***	-0.279***	-0.115*
		(-4.70)	(-4.70)	(-6.18)	(-6.21)	(-1.80)
Log(1+Buyer PatStock)	-	-0.094*	-0.090*	-0.121**	-0.126**	0.008
		(-1.75)	(-1.69)	(-2.25)	(-2.34)	(0.10)
Log(1+Seller PatStock)	+	0.280***	0.285***	0.281***	0.284***	0.172*
		(4.02)	(4.08)	(4.02)	(4.07)	(1.94)
Log(1+Buyer Cites)	?			0.179***		0.459***
				(3.25)		(4.90)
Frac. Cites from Buyer	?				0.213***	
					(4.06)	
Diff. SIC3	?					0.291
						(1.40)
Log(1+Buyer Cites)×Diff. SIC3	?					-0.497***
						(-4.41)
Year X Pat. Class FE		Yes	Yes	Yes	Yes	Yes
Observations		200,203	200,203	200,203	200,203	83,157
Adj. R^2		0.064	0.065	0.065	0.065	0.102
Avg. License Rate		2.071	2.071	2.071	2.071	2.192

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A Variable Definitions

Column 1 contains the name of the variable in the table. Column 2 contains the definition. Unless noted, all-cap variables indicate Compustat mnemonics. Patent citation data comes Google Patent Grants as of 2014. Unless time is explicitly subscripted, variables are defined contemporaneously, although they might be used with a lag. Lags are explicitly noted in tables. Variable transformations, when used, (e.g. log and standardizations) are described in the relevant tables. If noted, variables are winsorized at the 1% level annually.

Table I – firm year level

Assets	AT/GDPDEF (Normalized to 2009$ via BLS series GDPDEF)
Profits	OIBDP/GDPDEF
Patent Grants	From Kogan, Papanikolaou, Seru, and Stoffman (2012)
R&D Expenses	XRD/GDPDEF

Table II – firm year level

$R\&D_t/AT_{t-1}$	XRD_t/AT_{t-1} (winsorized)
$CAPX_t/AT_{t-1}$	$CAPX_t/AT_{t-1}$ (winsorized)
$Advertising_t/AT_{t-1}$	XAD_t/AT_{t-1} (winsorized)
Grants	Flow, from Kogan, Papanikolaou, Seru, and Stoffman (2012)
Cites	Flow of citations received on internally granted patents
Originality	Originality of citations of new patent grants, computed from Google Patent Grant citations, as defined in Hall, Jaffe, and Trajtenberg (2001)
PatAcq (CW)	Flow of patents acquired (bought or in-licensed), citation weighted pre-transaction
PatDiv (CW)	Flow of patents divested (sold or out-licensed), citation weighted pre-transaction
NewPatStock	Flow of patent grants plus flow of citations (*Grants + Cites*)
Total Q	From Peters and Taylor (2016) (winsorized)
Cash Flow	As defined in Chang, Dasgupta, Wong, and Yao (2014) (winsorized)
Log(Assets)	Log(AT)

Table IV – firm year level
See Table II for remaining variables

R&D	XRD_t/AT_{t-1} (winsorized)
CAPX	$CAPX_t/AT_{t-1}$ (winsorized)
Advertising	XAD_t/AT_{t-1} (winsorized)
Log(Assets)	Log(AT)

Table V – firm year level
All variables defined under Table IV

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Table VI – firm year level

See Table II for remaining variables

PatAcq	Shorthand for PatAcq (CW) (See Table II)
PatDiv	Shorthand for PatDiv (CW) (See Table II)
NetAcq	PatAcq minus PatDiv
K_{INT}	From Peters and Taylor (2016) (winsorized before log transformation)
PatStock (CW)	Citation weighted patent stock. Depreciation set to 15%.
R&D	XRD_t/AT_{t-1} (winsorized)
ProdMktFluidity	From Hoberg, Phillips, and Prabhala (2014)
TechPeerLit	Count of patents litigated in years $t-4$ to t among TNIC peer firms. TNIC peer groups from Hoberg and Phillips (2010a) and Hoberg, Phillips, and Prabhala (2014). Litigation data from Henry and Turner (2006) and Henry, McGahee, and Turner (2013).
Sales Growth	($SALE_t$ / $SALE_{t-1}$) -1 (winsorized)
Patent Growth	Log($Grants_t$) - Log($Grants_{t-3}$)
Delaycon	Hoberg and Maksimovic (2015)
MTR-BCG	From Blouin, Core, and Guay (2010)

Table VII – transaction level

Variables set to zero if missing and a variable is included for these observations and zero otherwise.

Patents in Deal	Number of patents in the transaction
Patent Age	Average age of the patents in the transaction
Previous Cites	Total number of preexisting citations received by patents in the deal as of the transaction date
Patent XRET	Borrows from Kogan, Papanikolaou, Seru, and Stoffman (2012). For each patent in a deal, obtain the grant firm's XRET (from CRSP) on the patent grant day. If the firm obtained multiple patents,given each equal credit for XRET, i.e. XRET/# patents firm was granted that day. For the transaction, take the maximum of this across patents in the deal.
Any Previous Cites by Buyer	1 if the buyer had cited any patents in the deal by the transaction date
Any Previous Cites by Seller	1 if the seller had cited any patents in the deal by the transaction date

Table VIII – transaction level

Variables set to zero if missing and a variable is included for these observations and zero otherwise.

License	1 if license, 0 if sale (see Appendix IA.A)
Tax Differential (Seller-Buyer)	Marginal tax rate of seller minus buyer. Data from Blouin, Core, and Guay (2010).
Buyer DelayCon	Buyer's Delaycon (See Table VI)
Buyer Eqty DelayCon	Buyer's Eqty Delaycon, from Hoberg and Maksimovic (2015)
Buyer Debt DelayCon	Buyer's Debt Delaycon, from Hoberg and Maksimovic (2015)
Buyer PatStock	Buyer's PatStock (See Table VI)
Seller PatStock	Seller's PatStock (See Table VI)
Buyer Cites	Number of times the buyer had cited the patents in the deal before the deal
Frac. Cites from Buyer	Number of times the buyer had cited the patents in the deal before the deal divided by total citations the patents had received
Diff. SIC3	1 if the buyer and seller were in a different SIC3 code. Defined for public-public transactions only.

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Internet Appendix for "Innovation Acquisition, Investment, and Contracting"

Donald E. Bowen III

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This appendix contains additional material not reported in the paper to preserve space. Section IA.A describes the construction of the dataset containing patent transactions. Section IA.B reports additional tests and data.

IA.A Data

Section IA.A.I defines which records in the USPTO Patent Assignment Dataset (PAD) are sales and which are licenses. Section IA.A.II discusses the algorithm to merge COMPUSTAT firm identifiers for buyers and sellers. Section IA.A.III describes the construction of firm year variables from the transaction level data.

I Identifying sale and license transactions in PAD dataset

The USPTO Patent Assignment Dataset (PAD) is a newly released set of Stata files, containing the universe of patent assignments reported to the USPTO between 1980 and 2014. The dataset is described in a companion paper (Marco et al. (2015)). The dataset contains about 6.3 million patent assignments. Assignments record changes in ownership, collateral interests, merger transfers, sales, corrections to the record, and most commonly, initial assignments from the inventor-employee to their employing firm.

For researchers, the good news about the data is that patent transactions are usually recorded because assignments are not legally binding unless they are filed with the USPTO. In particular, "By statute, failure to record an assignment in the USPTO renders it void against any subsequent purchaser or mortgagee" (Marco, Myers, Graham, DAgostino, and Apple (2015, p. 6)). Furthermore, Serrano (2010) reports that interviews with patent lawyers support recording patent transfers as best practice. The bad news about the data is that many records are not sales or licenses, and the dataset does not contain links to firm identifiers, such as PERMNO, CUSIP, CIK, or GVKEY. Additionally, transactions are not flagged as sales or licenses explicitly.

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Thus, the first crucial task is identifying which of the 6.3 million assignments are sales and licenses. First, I identify transactions that are licensing agreements. These are assignments containing "LICENS" in the assignment description, and whose conveyance type (a PAD variable called *convey_ty*) is "other". I manually examine a random subset of these and find no false positives based on available information. Second, I identify transactions that are sales. Sales are a subset of the are remaining transactions in the dataset whose conveyance type is "assignment", "missing", and "other". However, these conveyance types contain non-sale transactions. In particular, most of these assignments are employee-firm transfers and some are transfers within a firm. The USPTO requires that patent applications filed before Sept 16, 2012 be issued to a human (Marco, Myers, Graham, DAgostino, and Apple (2015)). Hence, firms have the inventor employee receive the grant and immediately assign the patent to the firm. To remove these non-sales from the list of possible sales, I adapt the strategies of Ma (2015) and Serrano (2010), who use an earlier versions of the PAD dataset. Note that an *assignee* is receiving the patent rights in the assignment from the *assignor*. I standardize the name fields for the assignor and assignee and use the following procedure:[63]

1. I keep transactions whose conveyance type (*convey_ty*) is listed as "assignment", "missing", and "other". I drop any assignments already identified as licenses.

2. PAD contains an indicator variable equal to one if Marco et al. (2015) designated the assignment as an employer assignment based on the assignment's text description. However, they note that they designed this variable in a conservative way, meaning that while the false positive rate is low, the false negative rate (assignments that are employer transfers but not indicated as such) may be high. Thus, I take additional measures to eliminate internal firm transfers.

3. Following Serrano (2010), I drop transactions recorded on the day the patent is granted. These are virtually always employer assignments. However, this fails to account for employee-firm transfers if they file the assignment after the grant day. This prompts two more steps.

4. I drop transactions that meet three criteria. If the transaction (1) covers a single patent and (2) is that patent's first transaction, I check whether (3a) the assignee

[63] I use *stnd_compname*, a Stata command available at http://www-personal.umich.edu/~nwasi/programs which standardizes strings and is designed specifically to deal with firm names. I augment the program to handle foreign firm names and extraneous address information common to PAD entity names.

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name corresponds to the patent grant firm (as listed in the USPTO grant dataset, which ignores inventors that immediately transfer the patent) or (3b) the assignor name corresponds to the inventor (as listed in the HBS Patent Inventor Dataset). If all three conditions are satisfied, I drop the transaction. To compare the transaction assignee with the USPTO grant assignee and the transaction assignor with the inventor, I standardize all strings. In this step, I consider (3a) and (3b) as satisfied if the strings are exact matches.

5. I repeat the last step, but allow for small spelling errors. Specifically, I accept fuzzy matches where the Levenshtein distance is less than 10% of the average length of the two strings and where the average length of the two strings is larger than 10.

6. Finally, I drop transactions that are likely internal transfers. These are observations where the standardized assignee and assignor names are exact matches or fuzzy matches, using the same algorithm as before.

The resulting dataset contains approximately 350,000 transactions with 1.4 million patents. Some transactions are bundled sales and cross licenses. I deal with this issue in Section IA.A.III while producing firm-year counts of patent transactions. Next, I obtain firm identifiers for the assignors and assignees.

II Merging in firm identifiers

The PAD dataset has string variables containing the names of the assignment parties. To map these to firm identifiers, such as GVKEY, I utilize several sources of information containing firm names and firm identifiers. In each dataset, I standardize company names using the same procedure I use to clean the names in the PAD. Before attempting to merge in GVKEYs, I take the following steps:

1. I build a dataset mapping the *raw* name of the assignee in the PAD dataset to a GVKEY for a range of years. The basic idea is: For the 5.3 million assignments we previously discarded as inventor-firm transactions, we can merge in the firm identity from other common patent data sources. This will produce a large list of PAD names connected to firm identifiers, where even if the firm name is misspelled, without conducting any string matching. This *map* can then be applied to the 350,000 sales and licenses to obtain firm identiers. Call this the ***Direct Grant Map***.

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(a) I select transactions with one patent and coded as employer assignments.

(b) Optimally, the *Direct Grant Map* will be error free. To reduce possible errors, I keep transactions with only one assignee, and whose patent is only transferred only once during the sample. This is deliberately restrictive.

(c) I connect the patent number to a PERMNO via the comprehensive firm listing provided by Kogan, Papanikolaou, Seru, and Stoffman (2012).

(d) I connect the PERMNO to a GVKEY using a link table provided by WRDS. If a PERMNO has multiple GVKEYs, I pick the one whose data range includes the patent grant. If multiple options remain, discard.

(e) Standardize firm names and reduce the resulting list to unique assignee name-GVKEY units. For each pair, a name is matched to a GVKEY for a date range that covers inventor-employer assignments.

2. I build a dataset mapping the comprehensive set of firm names in "coleft.cik.c" to a GVKEY for a range of years. Call it the ***Coleft Map***.

   (a) Join in possible GVKEYs for each CIK in "coleft.cik.c" using a link table provided by WRDS.

   (b) Append a name-GVKEY list from the same WRDS link table.

   (c) Standardize firm names, and reduce to unique name-gvkey pairs. For each pair, a name is matched to a GVKEY for a valid date range given by the WRDS the link table.

3. I load all standardized PAD names. For each name, I compare it to all firm names in the *Coleft Map* that begin with the same first there characters. This comparison is done with a large set of fuzzy match functions. Some of these functions have very low false positive rates and some have very low false negative rates. After a random sampling procedure, I select a rule that uses multiple fuzzy match functions to designate which name pairs are considered matches. The key insight in this process is that some functions have even lower false positive rates conditioning on prior filters. The resulting map designates accepted matches. Call it the ***Scored Map***.

With these maps constructed, I load the dataset containing sales and licenses and merge in GVKEYs for assignees using the following steps, which are repeated for assignors:

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1. Using the *Direct Grant Map*, find exact matches and merge in their GVKEY for the transaction year. This is responsible for about 50% of all accepted matches.

2. Using the *Coleft Map*, find exact matches for assignees and merge in their GVKEY for the transaction year. If their GVKEY is still blank, update it. This is responsible for about 10% of all accepted matches.

3. Using the *Scored Map*, find fuzzy matches for assignees and merge in their GVKEY for the transaction year. If their GVKEY is still blank, update it. This is responsible for about 40% of all accepted matches.

The resulting dataset, at the transaction-patent level, contains firm identifiers for the buyers in 66% of transactions and for the sellers in 60% of transactions.

III Building firm-year transaction variables

The central tests in the paper are based on a firm year panel. To construct firm-year variables capturing patent market activities, I load the patent transaction dataset. I merge into this dataset the number of pre-transaction citations received by each transfered patent. Then, I count the number of patents and the number of citation weighted patents in which a firm receives rights (as the assignee in the transaction) in a given year.[64] I call these variables *PatAcq* and *PatAcq (CW)*, respectively. Repeating this for assignors results in *PatDiv* and *PatDiv (CW)*.

III.1 A small issue

The above step contains a few checks to ensure firms get appropriate credit for patent right transactions. The main issue is that this dataset contains bundled sales and cross-licenses. Imagine firm A sells patent 1 to firm B while firm B sells patent 2 to firm A at the same time. If the firms combined both sales into one assignment, the assignment likely lists each firm as both assignor (sell-side) and assignee (buy-side). Thus, the data for this assignment would look like:

[64] For these variables, I do not make the distinction between complete ownership and receiving licensing rights.

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Buyer	Seller	Patent
A	B	1
B	A	1
A	B	2
B	A	2

In this case, we might not know which parties are selling which patents and which parties are buying which patents. Thus, I take two steps to remove possible sources of erroneous attribution. First, in counting patent acquisitions, I drop any acquisition if the assignee received the initial grant of the patent because of the low likelihood that a firm sells a patent and buys it back later. Second, in counting patent divestitures, I drop any assignor where we can positively identify another seller as the original grant holder (and thus the prohibitively likely seller of that patent). In the above example, assuming A received the grant for patent 1 and B received the grant for patent 2, this procedure would completely solve the issue. In fact, this procedure will completely address all instances of erroneous attribution except cases where the patent is being sold a second time, in which case information about the original owner is irrelevant.

A second, smaller issue exists in the dataset, for which I implement a simple solution. In some instances, a sale is submitted separately by both parties. I drop repeated transactions between the same parties for the same patent and keep only the first instance. Additionally, I drop duplicates when a firm is listed as acquiring or divesting the same patent multiple times in a year.

IA.B Additional results

This section presents extra results and robustness tests to support the main paper.

- Table IA.1 presents the industry composition of patent acquisitions, sales and grants. The broad pattern is industries that receive the most patent grants also buy and sell patent rights most often. High R&D industries are well represented, as most acquisitions are in electronic components, computer equipment, drugs, scientific instruments, and computing services.

- Table IA.2 presents robustness tests for the main result on R&D in Table IV by varying the specification used. The main results are robust to: replacing the main variables

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with non-citation weighted versions; replacing *NewPatStock* with the main R&D determinants from the literature (*PatStock* and a measure of intangible capital); including the variables that predict firm-year acquisitions in a firm fixed effect specification (intangible capital and *Sales Growth*, per Table VI); accounting for quadratic firm age to capture life cycle issues; and including prior R&D growth.

- Table IA.3 presents robustness tests for the main result on R&D in Table IV by varying how the independent variable, R&D, is defined.

- Table IA.4 presents robustness tests for the main result on R&D in Table IV by varying the treatment of missing R&D observations and the sample selection criteria. Results become attenuated as the sample includes more firms for which R&D is less important, as would be expected if large fixed costs must be incurred to begin R&D programs.

- Table IA.5 presents robustness tests for the dynamic estimation results in Table V by varying the number of included lags in the R&D model. I test the alternative models against each other and find that models with one or two lags are rejected in favor of three or four lags.

- Table IA.6 presents robustness tests for the dynamic estimation results in Table V by varying the number of included lags in the CAPX model. I test the alternative models against each other and find that models with one or two lags are rejected in favor of three or four lags.

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Table IA.1: Industry shares of public firm innovation activity

This table reports the share of patent acquisitions, patent divestitures, and patent grants among public firms that are attributable to different industries.

		Acquisitions		Divestitures		Patent grants	
SIC Code	Industry	Fraction	Rank	Fraction	Rank	Fraction	Rank
	Panel A: By SIC2						
36	Electronic and Other Electrical Equipment and Components	26%	1	24%	1	28%	1
35	Industrial and Commercial Machinery and Computer Equipment	17%	2	17%	2	20%	2
28	Chemicals and Allied Products	15%	3	13%	4	14%	3
38	Measuring Instruments, Optical Goods, and Clocks	13%	4	15%	3	9%	4
73	Business Services	8%	5	7%	6	8%	6
37	Transportation Equipment	7%	6	8%	5	9%	5
34	Fabricated Metal Products	2%	7	2%	9	1%	11
48	Communications	2%	8	3%	7	2%	8
29	Petroleum Refining and Related Industries	1%	9	2%	8	3%	7
26	Paper and Allied Products	1%	10	1%	10	2%	9
	Panel A: By SIC3						
367	Electronic Components And Accessories	12%	1	9%	2	13%	2
357	Computer And Office Equipment	10%	2	11%	1	16%	1
283	Drugs	8%	3	6%	5	6%	4
737	Computer Programming, Data Processing, And Related Services	8%	4	7%	4	8%	3
366	Communications Equipment	7%	5	8%	3	6%	5
384	Surgical, Medical, And Dental Instruments And Supplies	5%	6	3%	8	2%	14
382	Laboratory Apparatus And Related Instruments	4%	7	3%	9	2%	16
371	Motor Vehicles And Motor Vehicle Equipment	4%	8	4%	7	5%	6
386	Photographic Equipment And Supplies	3%	9	5%	6	5%	7
372	Aircraft And Parts	3%	10	3%	10	3%	9

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Table IA.2: Robustness of main R&D specification

This table reports alternative specifications of Model 1 in Table IV, which focuses on the relationship between patent acquisitions and future investment and internal innovation output. Analysis is based on an OLS estimation of Equation 1. The firm-year sample is described in Table II. The dependent variable is R&D, normalized by lagged assets and multiplied by 100, so coefficients for these models should be interpreted in terms of percentage points. *PatAcq* and *PatDiv* are not citation weighted. *Grants* is the flow of grants a firm receives and is the *NewPatStock*'s analogue of not using citation weights in *PatAcq*. *Age* is defined as the fiscal year minus the first year with price data in Compustat. *R&D Growth*$_{t-1}$ is defined as $Log(R\&D_{t-1}/AT_{t-2}) - Log(R\&D_{t-2}/AT_{t-3})$ and is winsorized. The remaining variables are defined in Appendix A. *Total Q, Cash Flow,* and *Log(Assets)* are included but not reported. To facilitate interpretation, *PatStock (CW)*, $Log(1+K_{INT})$, *Sales Growth* and *R&D Growth* are standardized. Industry by year fixed effects absorb industry specific time trends, and firm fixed effects are included. T-statistics are reported in parentheses. Standard errors are clustered by firm. The symbols ***, **, and *, indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	R&D normalized by lagged assets, ×100							
Log(1+PatAcq (CW))$_{t-1}$	0.081***		0.079***		0.060**	0.051*	0.082***	0.085***
	(2.73)		(2.69)		(2.09)	(1.78)	(2.80)	(2.84)
Log(1+PatDiv (CW))$_{t-1}$	-0.102***		-0.105***		-0.102***	-0.088***	-0.102***	-0.100***
	(-3.31)		(-3.42)		(-3.46)	(-3.07)	(-3.32)	(-3.25)
Log(1+NewPatStock)$_{t-1}$		0.131**	0.134**			-0.255***	0.079	0.128*
		(1.97)	(2.02)			(-3.95)	(1.15)	(1.80)
Log(1+PatAcq)$_{t-1}$				0.093**				
				(2.04)				
Log(1+PatDiv))$_{t-1}$				-0.148***				
				(-3.53)				
Log(1+Grants)$_{t-1}$				0.512***				
				(6.56)				
Log(1+PatStock (CW))$_{t-1}$					-0.375***			
					(-5.20)			
Log(1+K$_{INT}$)$_{t-1}$					4.567***	4.346***		
					(19.07)	(16.95)		
Sales Growth$_{t-1}$						0.259***		
						(3.39)		
Firm Age$_{t-1}$							-0.153	
							(-0.00)	
Firm Age$^2_{t-1}$							-0.002**	
							(-2.01)	
R&D Growth$_{t-1}$								1.033***
								(17.61)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year × SIC3 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	51,983	51,983	51,983	51,983	51,983	47,349	51,983	43,076
Adj. R^2	0.74	0.74	0.74	0.74	0.75	0.75	0.74	0.76

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Table IA.3: Robustness to the definition of R&D

This table reports alternative specifications of Model 1 in Table IV, which focuses on the relationship between patent acquisitions and future investment and internal innovation output. Analysis is based on an OLS estimation of Equation 1. The firm-year sample is described in Table II. In column 1, the dependent variable is R&D normalized by lagged CAPX. In column 2, the dependent variable is R&D normalized by lagged sales. In columns 1 and 2, the dependent variable is multiplied by 100, so coefficients for these models should be interpreted in terms of percentage points. In column 3, the dependent variable is $Log(1 + R\&D)$. The first six independent variables are defined in Table IV and Appendix A. *Log(Sale)* is the log of sales. K_{INT} is defined in Table VI The variables defined as ratios (*R&D/CAPX, R&D/Sales, Total Q,* and *Cash Flow*) are winsorized at the 1% level annually. To facilitate interpretation, *Total Q, Cash Flows, Log(Assets), Log(Sale)*, and $Log(1 + K_{INT})$ are standardized. Industry by year fixed effects absorb industry specific time trends, and firm fixed effects are included. T-statistics are reported in parentheses. Standard errors are clustered by firm. The symbols ***, **, and *, indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	$100\times$R&D$_t$/CAPX$_{t-1}$	$100\times$R&D$_t$/Sales$_{t-1}$	Log(1+R&D)$_t$
Log(1+PatAcq (CW))$_{t-1}$	0.207**	0.044***	0.006***
	(2.28)	(4.28)	(2.87)
Log(1+PatDiv (CW))$_{t-1}$	-0.074	-0.017	-0.016***
	(-0.90)	(-1.51)	(-6.21)
Log(1+NewPatStock)$_{t-1}$	0.896***	0.239***	-0.022***
	(5.70)	(9.46)	(-4.34)
Total Q$_{t-1}$	-0.185*	-0.020	0.109***
	(-1.91)	(-0.91)	(18.15)
Cash Flow$_{t-1}$	-0.671**	0.146***	0.069***
	(-2.01)	(3.23)	(12.26)
Log(Assets)$_{t-1}$	-10.777***		
	(-11.62)		
Log(Sale)$_{t-1}$		-5.117***	
		(-17.21)	
Log(1+K$_{INT}$)$_{t-1}$			1.619***
			(55.36)
Year × SIC3 FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Observations	51,328	51,256	51,983
Adj. R^2	0.44	0.57	0.95

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Table IA.4: Sample selection and R&D treatment

This table reports alternative specifications of Model 1 in Table IV, which focuses on the relationship between patent acquisitions and future investment and internal innovation output. Analysis is based on an OLS estimation of Equation 1. The firm-year sample and all variables are described and defined in Table II. Column 1 replicates the baseline model. Each column then adds a new set of firms, where the the restriction of active R&D programs is gradually relaxed. In column 2, observations with zero R&D are allowed if the firm reported positive R&D at any other point. In column 3, all observations with zero R&D are allowed. In column 4, observations are allowed if the firm reported positive R&D at any point and missing R&D is set to zero. In column 4, all observations are allowed and missing R&D is set to zero. To facilitate interpretation, *Total Q, Cash Flows, Log(Assets)*, *PatStock (CW)*, and $Log(1 + K_{INT})$ are standardized. Industry by year fixed effects absorb industry specific time trends, and firm fixed effects are included. T-statistics are reported in parentheses. Standard errors are clustered by firm. The symbols ***, **, and *, indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	R&D normalized by lagged assets, $\times 100$				
Log(1+PatAcq (CW))$_{t-1}$	0.079***	0.080***	0.079***	0.050*	0.024
	(2.69)	(2.69)	(2.68)	(1.78)	(1.07)
Log(1+PatDiv (CW))$_{t-1}$	-0.105***	-0.108***	-0.106***	-0.098***	-0.070***
	(-3.42)	(-3.52)	(-3.48)	(-3.45)	(-3.03)
Log(1+NewPatStock)$_{t-1}$	0.134**	0.126*	0.121*	0.072	-0.001
	(2.02)	(1.89)	(1.83)	(1.18)	(-0.03)
Total Q$_{t-1}$	0.445***	0.459***	0.461***	0.416***	0.422***
	(4.64)	(4.82)	(4.83)	(4.55)	(5.18)
Cash Flow$_{t-1}$	-2.798***	-2.807***	-2.800***	-2.760***	-2.601***
	(-19.28)	(-19.38)	(-19.34)	(-19.41)	(-19.94)
Log(Assets)$_{t-1}$	-9.884***	-9.658***	-9.580***	-8.125***	-5.877***
	(-25.29)	(-24.91)	(-24.89)	(-23.72)	(-22.30)
Year × SIC3 FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Observations	51,983	52,530	53,556	59,562	75,198
Adj. R^2	0.74	0.74	0.74	0.74	0.76
Sample condition:	R&D$_t > 0$	R&D> 0 during sample	R&D not missing	R&D > 0 during sample	All
Treatment of missing R&D:	Missing	Missing	Missing	Zero	Zero

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Table IA.5: Dynamic lag selection in the R&D model

This table reports alternative specifications of Model 1 in Table V, which focuses on the dynamic relationship between patent acquisitions and future investment and internal innovation output. Analysis is based on an OLS estimation of Equation 2. The firm-year sample and variable definitions are described in Table II. The dependent variable is R&D normalized by lagged assets and multiplied by 100, so coefficients for these models should be interpreted in terms of percentage points. Likelihood ratio p-values are reported containing tests of against each nested model. Rejecting the null implies the larger model fits the data better. Firm-year level controls *Total Q, Cash Flows,* and *Log(Assets)* are not reported for brevity. Industry by year fixed effects absorb industry specific time trends, and firm fixed effects are included. T-statistics are reported in parentheses. Standard errors are clustered by firm. The symbols ***, **, and *, indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	R&D			
	(1)	(2)	(3)	(4)
Log(1+PatAcq (CW))$_{t-1}$	0.079***	0.075**	0.091***	0.071**
	(2.69)	(2.56)	(3.04)	(2.44)
Log(1+PatAcq (CW))$_{t-2}$		0.043	0.016	0.004
		(1.51)	(0.57)	(0.14)
Log(1+PatAcq (CW))$_{t-3}$			0.108***	0.088***
			(3.50)	(2.94)
Log(1+PatAcq (CW))$_{t-4}$				0.036
				(1.09)
Log(1+PatDiv (CW))$_{t-1}$	-0.105***	-0.099***	-0.106***	-0.101***
	(-3.42)	(-3.29)	(-3.53)	(-3.41)
Log(1+PatDiv (CW))$_{t-2}$		-0.046	-0.036	-0.022
		(-1.44)	(-1.22)	(-0.74)
Log(1+PatDiv (CW))$_{t-3}$			-0.068**	-0.061**
			(-2.23)	(-2.07)
Log(1+PatDiv (CW))$_{t-4}$				-0.003
				(-0.08)
Log(1+NewPatStock)$_{t-1}$	0.134**	0.101	0.105	0.091
	(2.02)	(1.47)	(1.46)	(1.23)
Controls	Yes	Yes	Yes	Yes
Year × SIC3 FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Observations	51,983	47,813	43,893	40,159
Adj. R^2	0.74	0.75	0.75	0.75
Likelihood ratio p-values:				
Relative to null of model (1):		0.78	0.01	0.03
Relative to null of model (2):			<0.01	0.01
Relative to null of model (3):				0.51

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Table IA.6: Dynamic lag selection in the CAPX model

This table reports alternative specifications of Model 1 in Table V, which focuses on the dynamic relationship between patent acquisitions and future investment and internal innovation output. Analysis is based on an OLS estimation of Equation 2. The firm-year sample and variable definitions are described in Table II. The dependent variable is CAPX normalized by lagged assets and multiplied by 100, so coefficients for these models should be interpreted in terms of percentage points. Likelihood ratio p-values are reported containing tests of against each nested model. Rejecting the null implies the larger model fits the data better. Firm-year level controls *NewPatStock, Total Q, Cash Flows,* and *Log(Assets)* are not reported for brevity. Industry by year fixed effects absorb industry specific time trends, and firm fixed effects are included. T-statistics are reported in parentheses. Standard errors are clustered by firm. The symbols ***, **, and *, indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	CAPX			
	(1)	(2)	(3)	(4)
Log(1+PatAcq (CW))$_{t-1}$	0.026	0.015	0.019	0.011
	(1.39)	(0.82)	(1.03)	(0.60)
Log(1+PatAcq (CW))$_{t-2}$		0.036*	0.032*	0.028
		(1.93)	(1.74)	(1.48)
Log(1+PatAcq (CW))$_{t-3}$			0.049**	0.042**
			(2.49)	(2.15)
Log(1+PatAcq (CW))$_{t-4}$				0.043**
				(1.97)
Log(1+PatDiv (CW))$_{t-1}$	-0.085***	-0.087***	-0.087***	-0.091***
	(-4.27)	(-4.56)	(-4.58)	(-4.79)
Log(1+PatDiv (CW))$_{t-2}$		-0.048**	-0.047**	-0.040**
		(-2.43)	(-2.42)	(-2.11)
Log(1+PatDiv (CW))$_{t-3}$			-0.052***	-0.050***
			(-2.75)	(-2.66)
Log(1+PatDiv (CW))$_{t-4}$				-0.036*
				(-1.81)
Controls	Yes	Yes	Yes	Yes
Year × SIC3 FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Observations	51,983	47,813	43,893	40,159
Adj. R^2	0.40	0.41	0.42	0.43
Likelihood ratio p-values:				
Relative to null of model (1):		0.07	<0.01	<0.01
Relative to null of model (2):			<0.01	<0.01
Relative to null of model (3):				0.15

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