Free up (Burdened) Resources: An Empirical Examination of Secondary Market Patent Transactions

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Abstract

In this paper, I study patent transactions from public assignors (seller firms) to assignees (buyer firms). I first show that firms with higher innovation productivity (more able to innovate) but with lower production efficiency (less able to commercialize) are more likely to sell patents distant from their operations. Using a linked assignor-assignee dataset, I find that patents technologically closer to buyer than to seller firms are more likely to be sold in a patent transaction, implying gains from trading patents. I document that, seller firms experience a significant improvement in their ROA and operating profitability over the three years following patent transactions. I find that the improvement in ROA and operating profitability is more pronounced in seller firms which increase their R&D focus after patent transactions, suggesting that an increase in innovation focus is one of the channels underlying these results. Consistent with this channel, I find that (a) inventors who are either newly hired by or remaining in seller firms over the three years subsequent to patent transactions have technological expertise more similar to those of seller firms, and that (b) seller firms generate new patents closer to their main line of businesses following the transactions. Overall, my paper sheds new light on the importance of secondary market of patents for facilitating knowledge flows and reallocating firms' innovation resources.

Keywords: Patent Transactions; Patent Selling; Corporate Innovation; Corporate Refocusing

EFM Classification: 210

1. Introduction

How do firms manage their patent portfolios? An important way for firms to efficiently manage their patent portfolios is through a well-functioning secondary market for patents. Such a secondary market is critical not only to firms but also to the economy at large. By allowing firms with different comparative advantages to specialize in R&D and commercialization, an efficient secondary market for patents enables a more productive use of the existing technology and provides further incentives for firms to invest in R&D. This could be beneficial to firms' long-term growth. For policymakers and the whole economy, an efficient secondary market is equally important. A well-functioning secondary market for patents is critical for diffusing innovation and curtailing duplicate R&D efforts. Moreover, it also improves social welfare by enabling patents to be used by more efficient market participants.

Over the past decade, researchers have gained considerable insight into the factors that affect the innovation productivity of firms.[1] However, how firms manage their innovation output (i.e., patents) after they are developed remains largely underexplored. When hiring research staff to conduct in-house R&D activity, firms usually promise research freedom and give research personnel large discretion in the specifics of the projects they can work on. This decentralized R&D process, combined with the uncertain nature of new inventions, often leads to researchers employed by a firm generating patents that may not all be an exact fit with the firm's needs. As a result, among the patents in a firm's patent portfolio, the firm may choose to commercialize only a part of them that are closely related to its main line of business while leaving the remaining patents "sitting on the shelf".

The above situation raises a number of research questions that I explore in this paper. First, what are the determinants of innovative firms selling some of their patents to others? When these innovative firms sell some of their patents, which patents do they choose to sell? Second, what are the implications of secondary market patent transactions for the future economic and financial

[1] For example, see Manso (2011), Ederer and Manso (2013), Aghion, Van Reenen and Zingales (2013), Chemmanur, Loutskina and Tian (2014), and Tian and Wang (2014)), among others.

performance of seller firms? This paper aims to address these questions.

The secondary market for patents has grown significantly over the last several decades. Figures 1 and 2 give an overview of this landscape. Figure 1 shows the number and percentage of innovative firms (both private and public) selling their patents in the secondary market from 1980 to 2017. The number of firms selling patents prior to 1980 was small. However, this number has grown dramatically since then and has remained steady in the last decade. We can also observe an upward trend in the percentage of innovative firms selling patents. Figure 2 displays the number of patents sold in the secondary market from 1980 to 2017. The magnitude is also large. Notably, the number of patents being traded (excluding those traded due to other reasons, such as mergers & acquisitions, mortgage, security interest etc.) has risen over 120,000 in 2014, which is approximately over a third of the new patents granted in the U.S. in the same year. These figures, taken together, point to a very large and stable secondary market for patents. However, there have been few attempts so far in the literature to gain a thorough understanding of the secondary market for patents as well as its implications for firms. My paper aims to fill this gap in the literature.

Prior to my empirical analysis, I develop testable hypotheses based on the existing theoretical literature and new conjectures on my part. First, I develop testable hypotheses regarding the determinants of secondary market patent transactions for seller firms. Innovation has long been argued to be critical to firms' long-term growth. Innovative firms constantly conduct innovation activity so that they can build valuable products around their innovation output and gain an advantage in the product market. Throughout the process of innovative firms developing their innovation output, high-quality inventors play a pivotal role. In order to attract high-quality research personnel, apart from offering a competitive salary and other compensations, an innovative firm usually promises research freedom and does not put many restrictions on the specifics of the projects the research personnel could work on. During this decentralized R&D process, combined with the uncertain nature of new inventions, the research staff of a firm may not always come up with innovation output (in the form of patents) that perfectly aligns with the firm's main line of business. If some of the developed patents are far away from the firm's operations, they could be very costly to commercialize, since the firm needs different complementary technology and assets in place before it can commercialize such patents and release the final products to the market.

Therefore, based on this argument, I conjecture two sets of determinants (firm-level and patent-level) of secondary market patent transactions of seller firms. In terms of the firm-level determinants of patent transactions of seller firms, I hypothesize that firms with higher innovation productivity (i.e., more able to innovate) but with lower production efficiency (i.e., less able to commercialize their innovation output) are more likely to sell some of their patents. In terms of the patent-level determinants, I posit that patents that are less relevant to a seller firm's operations are more likely to be sold in a patent transaction. In addition, the closeness of a patent to a buyer firm's operations also matters for the probability of the patent to be sold in a patent transaction. Thus, I hypothesize that patents that are relatively closer to the assignees (buyers) than to the assignors (sellers) firms are more likely to be sold in the secondary market.

Second, I develop testable hypotheses regarding the economic and financial consequences of secondary market patent transactions for assignor firms. The effect of patent transactions on seller firms' future operating performance is ambiguous *ex ante*. Whether a secondary market patent transaction increases or decreases a seller firm's long-run operating performance depends on whether commercializing the patent in-house is a positive or a negative NPV transaction. If commercializing a patent in-house is very costly, selling it to another firm and thus monetizing the value of the patent to some extent (rather than letting it sit on the shelf) will increase a seller firm's operating performance. Further, selling patents further away from its core activity also means that the seller firm is increasing its R&D focus. This leads to the seller firm innovating more in areas closer to its expertise and utilizing its R&D resources more efficiently in the future. This will also result in an increase in the firm's operating performance following the selling of a patent. However, by re-assigning the entire rights and ownership of a patent to others, a seller firm would lose control of where this patent flows and how this patent will be used in the future. If this patent ends up in the portfolio of a product market competitor of the seller firm, or if this patent flows to a buyer firm that uses products/services provided by a product market competitor of the seller firm, this may result in greater product market competition. This increased product market competition may cannibalize the seller firm's market share and its product market advantage, which, in turn, may lead to a decline in the operating performance of the seller firm following the patent transaction. In sum, the effect of patent transactions on seller firms' subsequent operating performance could be positive or negative, and hence determining its effect is ultimately an empirical question.

I test the above hypotheses using a unique dataset of secondary market patent transactions collected from the USPTO. This unique data, namely the USPTO Patent Reassignment Dataset, is compiled by the Office of Chief Economist of the USPTO and spans from 1970 to 2019. It contains detailed information about over 8 million patent transactions in the secondary market that affect a patent's title (e.g., patent reassignments and patent transfers as a result of M&As) or that are relevant to patent ownership (e.g., patent licensing, security agreements, and others). In this paper, I focus only on between-firm patent reassignments, where patents are sold by assignor (i.e., seller) to assignee (i.e., buyer) firms. By merging this data with other standard datasets often used in the corporate innovation literature, I am able to explore the determinants and consequences of secondary market patent transactions from seller firms' points of view. In addition, by using a linked assignor-assignee dataset, I also test my hypothesis regarding the relationship between the relative distance of a patent from the assignor versus the assignee and the probability of the patent to be sold in a patent transaction.

The findings of my empirical analyses can be summarized as follows. First, at the firm level, I find that firms with higher innovation quantity (as proxied by the number of patents a firm applies for during a certain period that are eventually granted) or innovation quality (as proxied by the number of citations per patent for the patents applied by a firm during a certain period) are more likely to sell some of their patents. In addition, firms with lower prior production efficiency (used as a proxy for firms' commercialization efficiency) are more likely to sell some of their patents in the subsequent year. This effect is greater for firms with higher innovation quantity or quality.

Second, at the patent level, I find that a patent more technologically distant from a seller firm's operations is more likely to be sold. This effect is stronger for firms with a larger number of patents in their patent portfolio. Further, in my empirical analysis using a linked assignor-assignee dataset, I find that a patent technologically closer to a buyer than to a seller firm is more likely to be sold in a patent transaction, implying there are gains from trading the patent by the seller to the buyer firm.

Third, I turn to the economic and financial consequences of secondary market patent transactions. Using a matched sample of seller and non-seller firms, I find that seller firms, on average, experience a positive and statistically significant improvement in their ROA and operating profitability over the three years after selling some of their patents. To delve deeper and gain a better understanding of the sources of increase in seller firms' ROA, I explore separately the effect of secondary market patent transactions on individual components of ROA, as well as its effect on firm-level total factor productivity (TFP). I find that seller firms increase their sales and decrease their overhead costs following patent transactions. More importantly, over the next three years following patent transactions, seller firms experience a significant improvement in their total factor productivity (TFP). Using a difference-in-differences (DiD) framework based on the 1999 American Inventors Protection Act as an exogenous shock to the patent transaction incidence, I provide causal interpretation of the baseline results regarding the consequences of secondary market patent transactions.

By utilizing a triple-DiD model to investigate the heterogenous treatment effect of patent transactions, I find that the improvement of operating performance is concentrated in seller firms which increase their R&D focus following patent transactions, suggesting that an increase in the innovation focus of seller firms is an important mechanism driving my results. Further supporting this channel, I examine the expertise of seller firms' inventors, as well as seller firms' innovation productivity and patenting behavior following the patent transactions. I first find that inventors who are either newly hired by or remaining in assignor firms over the three years subsequent to patent transactions have technology expertise more similar to assignor firms' own technology expertise, compared to those hired by or remaining in assignor firms in other periods. In addition, I document that, following the patent transactions, seller firms increase their patenting activity (as evidenced by them generating a larger number of patents) and also generate patents that are technologically closer to their main line of businesses.

The rest of the paper is organized as follows. Section 2 discusses the related literature. Section 3 outlines the underlying theory and develops some testable hypotheses. Section 4 describes the data used in my study and details the construction of some key variables. Section 5 presents the results on the determinants of patent transactions from the seller firms' perspective. Section 6 presents the results on the financial consequences of patent transactions for seller firms. Section 7 concludes.

2. Relation to the Existing Literature and Contribution

My paper contributes to several strands of literature. The first strand of literature related to my paper is on the market for technology.[2] Serrano (2010) studies the secondary market for patents at the patent level. He provides a theoretical model of patent transfers and renewals and develops some empirical analysis of the transfers and renewals of patents. While he documents that the probability of a patent being traded depends on the age of the patent and the number of citations received by a

[2] See also Kwon et al. (2020) who analyze the patent transactions in the biotechnology industry only.

given age, he does not study any of the issues I analyze here, such as the determinants of an assignor firm selling patents or the economic and financial consequences of such patent sale. In their theory paper, Akcigit et al. (2016) build an endogenous growth model where an innovative firm develops various innovation ideas at different points in time. In this model, some of the ideas (patents) developed by the firm are closer to its operations and hence could contribute more to the firm's productivity, while others may be further away from its operations; the firm can sell these patents. In an unpublished working paper, Bowen (2016) studies the secondary market for patents from the buyers' point of view (i.e., a mirror image of what I do in this paper, which is studying the secondary market for patents from the sellers' perspective). He documents that firms purchase patents to complement their R&D rather than substitute for it. Ma et al. (2022) study innovative firms in bankruptcy. They find that firms sell the core patents in their patent portfolio after filing for Chapter 11 reorganization. Different from the above papers, my paper is the first large-sample study to focus on the secondary market for patents from the assignor firms' perspective and to study the causes and economic and financial consequences of patent transactions for assignor firms.

Second, my paper extends the broader literature on corporate innovation (e.g., Manso (2011), Aghion, Van Reenen and Zingales (2013), Chemmanur, Loutskina and Tian (2014), Tian and Wang (2014), Brav, Jiang, Ma and Tian (2018), Chemmanur, Kong, Krishnan and Yu (2019) and others). The existing literature focuses on how different firm characteristics, organizational forms, and regulations affect the success of corporate innovation activities. My paper is different from these papers, since I focus on how firms deal with their innovation output (i.e., patents) once they are developed and how this will affect the future economic and financial performance of firms.

Third, my paper is related to the literature on asset sales or reallocation of assets (e.g., John and Ofek (1995), Maksimovic and Philips (1998), Bernstein, Colonnelli and Iverson (2019), and others). This strand of literature focuses mostly on the sale or allocation of tangible assets. Different from this literature, my paper studies the firms' decisions to sell or reallocate their intangible assets (specifically, patents) and the economic and financial consequences of such decisions for firms.

Fourth, my paper is distantly related to the literature on non-practicing entities, or "patent trolls" (e.g., Cohen, Gurun, and Kominers (2019), Appel, Farre-Mensa, and Simintzi (2019), Abrams, Akcigit, Oz, and Pearce (2019) and others). Existing literature on patent trolls mostly focuses on how patent trolls affect firms' innovation and employment. However, my paper focuses on assignor firms in the secondary market for patents. These firms are fundamentally different from patent trolls for two reasons. First, patent trolls usually acquire patents and license them to other firms. In other words, they are more likely to be assignee rather than assignor firms in patent transactions. Second, the baseline sample of my study is Compustat public firms. Since patent trolls do not have any real operations or production and profit mainly from exerting patent rights against infringements, they are unlikely to appear in my sample.

3. Theory and Hypothesis Development

In this section, I discuss the underlying theory and develop some testable hypotheses. I first develop hypotheses regarding the determinants of patent transactions from assignor firms' perspective. Innovation has long been argued to be critical to a firm's long-term growth. Firms with high innovation capacity can build valuable products around their innovation output and use them to gain an advantage in the product market. Throughout the process of a firm developing its innovation output, high-quality inventors play a pivotal role. In order to attract the finest research personnel, apart from offering a competitive salary and other compensations, a firm usually promises research freedom and does not put many restrictions on the specifics of the projects the research personnel could work on. During this decentralized R&D process, the research staff of the firm may not always come up with innovation output (in the form of patents) that perfectly aligns with the firm's main line of business.[3] As a result, among all the patents in a firm's patent portfolio, the firm may choose to commercialize only a part of them that are closely related to its main line of business, while leaving the remaining patents "sitting on its shelf". These "sitting-on-the-shelf" patents may be far away from the firm's operations and hence could be very costly to commercialize, since the firm needs different complementary technology and assets in place before it can commercialize an invention and release the final product to the market.

Therefore, based on the above argument, I hypothesize that firms with higher innovation productivity (i.e., more able to innovate) but with lower production efficiency (i.e., less able to commercialize all of their innovation output) can sell some of the patents.[4] In addition, I conjecture that the effect of production efficiency on the probability of firms selling patents will be greater for those with higher innovation productivity. This is because these firms will have a greater degree of flexibility to decide which patent to sell when their production efficiency is lower and hence cannot efficiently utilize all the patents. This argument leads to the following two testable hypotheses.

Hypothesis 1: Firms with greater innovation quantity or innovation quality are more likely to sell some of their patents in a patent transaction.

Hypothesis 2: Firms with lower production efficiency are more likely to sell some of their patents. The effect of production efficiency on the probability of firms selling patents increases with firms' innovation productivity or innovation quality.

In terms of the patent-level determinants of patent transactions, I hypothesize that a seller firm

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[3] This point can be best illustrated by a statement from Scott Frank, President and CEO of AT&T Intellectual Property, after AT&T sold one particular patent to Uber in 2017. This patent is titled "Methods and Systems for Routing Travel Between Origin and Destination Service Locations Using Global Satellite Positioning". Scott commented on the deal: "AT&T has one of the world's great research operations, with thousands of talented scientists and engineers breaking new ground in a variety of fields. But not all of these inventions end up being deployed in our core business..."

[4] Another real-world patent transaction that seems to be in line with this argument is the sale of patents by IBM to Alibaba. On Sep 30, 2013, International Business Machine (IBM) Corporation sold 22 patents to Alibaba. One patent is particularly relevant to Alibaba's main line of business (while distant from IBM's operations), which is titled "Automatic Sales Promotion Selection System and Method" (patent number: 5774868). This patent was invented by employees of IBM and was assigned to IBM in the first place, which was later sold to Alibaba in this patent transaction. This patent appears to be closer to Alibaba's main line of business (i.e., online shopping and promotion) than to IBM's main operation.

is more likely to sell in a patent transaction a patent distant from its main line of business. A firm's existing patent portfolio defines the knowledge space in which the firm specializes and operates. If a patent is located further away from the knowledge space of the firm, the patent is more likely to be a poor fit with the firm's operations and hence would not be efficiently commercialized. Further, the effect of the technological distance of a patent on the probability of it to be sold would be greater for firms with higher innovation productivity (i.e., a larger number of patents in their patent portfolios). This is because firms with higher innovation productivity have a greater degree of flexibility in deciding which patent to sell. They are thus more likely to sell patents distant from their operations to recoup the cost of developing them in the first place.

However, in a patent transaction, a patent distant from the knowledge space of the assignor firm could be, at the same time, even further away from that of the assignee firm, suggesting the relative technological distance of a patent (between the seller and the buyer firm) could also play a role in determining the probability of the patent to be sold. I argue that the technological distance of a patent can be viewed as a measure of the patent's fit with a firm's operation. If a focal patent is technologically closer to a buyer than to a seller firm, then the buyer can create greater value making use of the patent than the seller can. In this case, there are gains from trading (or selling) the patent by the seller to the buyer firm, in exchange for a fraction of the greater value (in the form of financial returns) created by the buyer firm using that patent. The aforementioned argument leads to the following testable hypotheses.

Hypothesis 3: A patent distant from a seller firm's main operations is more likely to be sold in a patent transaction. This effect will be greater for firms with higher innovation productivity.

Hypothesis 4: A patent technologically closer to a buyer than to a seller firm is more likely to be sold in a patent transaction.

The third set of hypotheses is regarding the firm-level consequences of patent transactions. The effect of patent transactions on seller firms' future operating performance is ambiguous *ex ante*. On the one hand, seller firms may experience an improvement in their operating performance following patent sales. By selling patents to buyer firms, sellers will be able to monetize the value of patents to some extent (rather than letting the patents sleep on the shelf), which could lead to increased operating performance. In addition, by selling patents less relevant to their core business, seller firms increase their innovation focus after the patent transactions. If seller firms increase their R&D focus and innovate more in the areas in which they specialize subsequent to the patent transactions, this will lead to the management and research personnel of seller firms allocating and utilizing their R&D resources in a more efficient and focused way. The more efficient use of their R&D resources (and hence an increase in focus) is then reflected in the improvement of the seller firms' operating performance following the patent transactions. On the other hand, patent transactions could be associated with a decrease in the seller firms' future operating performance. By re-assigning the entire rights of a patent to others, a seller firm would not have any control of how this patent will be used in the future. If this patent flows into the portfolio of a product market competitor of the seller firm, this may induce greater product market competition for the seller firm. This increased product market competition may cannibalize the seller firm's market share and its product market advantage, which, in turn, may lead to a decline in its operating performance following the patent transaction. Therefore, I develop the following two opposing hypotheses with respect to the firm-level consequences of patent transactions.

Hypothesis 5A: The operating performance of seller firms improves following the patent transactions.

Hypothesis 5B: The operating performance of seller firms declines following the patent transactions.

4. Data and Sample Selection

4.1 Sample and Data Sources

The baseline sample of my study is Compustat innovative firms. The innovative firms in my study are defined to be those that have an active R&D program or have filed for at least one patent (that is eventually granted) during the sample period. I study patent transactions from year 1980 to 2017. My sample starts at the year 1980 because the data on secondary market patent transactions prior to 1980 is scarce. My sample ends at the year 2017 because I want to study the three-year operating performance of a seller firm after a patent transaction, so I need a 3-year gap between the last date of my patent transaction dataset and that of the Compustat firm fundamentals dataset. In addition, I focus on patent transactions of non-financial firms, so firms with SIC code 6000-6799 are excluded from my sample.

The data used in my study comes from several sources. The main source from which the patent transaction-related information is collected is the United States Patent and Trademark Office (USPTO) Patent Assignment Dataset. In 37 CFR (Code of Federal Regulations) 3.1, an assignment of a patent is defined as the transfer to another of a party's entire ownership interest or a percentage of that party's ownership interest in the patent. It should be noted that recording patent assignments at USPTO is not mandatory. However, such recording is recommended by both patent statute and federal regulations, since it ensures the buyer's proper ownership of the focal patent or patent application. According to 35 U.S.C. (United States Codes) 261, "…an interest that constitutes an assignment, grant, or conveyance shall be void as against any subsequent purchaser or mortgagee for valuable consideration, without notice, unless it is recorded in the Patent and Trademark Office within three months from its date or prior to the date of such subsequent purchase or mortgage…" Therefore, the patent reassignment data collected from USPTO should have a relatively good coverage of the secondary market patent transactions in the U.S.

The USPTO Patent Assignment Dataset is compiled by the Office of Chief Economist of the USPTO.[5] This comprehensive dataset covers the period from 1970 to 2019. It has detailed

[5] See Marco et al. (2015) for a thorough explanation of this dataset.

information about 8.6 million patent transactions in the secondary market that affect a patent's title (e.g., patent assignments and patent transfers as a result of M&As) or are relevant to patent ownership (e.g., patent licensing, security agreements, and others). This dataset contains information about assignors (i.e., seller) firms and assignees (i.e., buyer) firms, patents involved in every transaction, types of different transactions, and the transaction execution dates.

In this study, I focus on between-firm patent reassignments, so I exclude cases of patent transfers as a result of corporate M&As, as well as other patent transactions relevant to patent ownership (e.g., patent licensing, name change, security agreements, mortgages, and others). Further, in the case of patent assignments, I remove two types of within-firm patent transfer. The first type is the employer assignment. According to the U.S. patent laws, for all patent applications filed before September 16, 2012, the granted patents must be issued to human inventors.[6] Inventors who work in a firm are usually contractually obligated to transfer their interests and ownership of granted patents to their employers. One example of employer assignment is from Philip Barrett and others to the Microsoft Corporation on November 10, 1988.[7] The involved patent (patent number: 4974159) is titled "Method of Transferring Control in a Multitasking Computer System". This type of patent assignment is essentially a within-firm transfer, since it does not alter the ownership status of a patent beyond a firm's boundary. So, this type of patent assignment is excluded from my sample.

The second type of within-firm patent transfer I remove from my sample is the transfer of patents between different subsidiaries of the same parent firm. This type of patent assignment arises primarily due to tax considerations.[8] A typical example of this type of patent assignment is the transfer of a patent between different subsidiaries of the Dow Inc.[9] The patent (patent number:

[6] This condition does not hold after September 16, 2012.
[7] The reel frame id for this patent assignment is 4974/870.
[8] For example, Dischinger and Riedel (2011) document that multinational firms have an incentive to locate their intangible assets at affiliates with a relatively low corporate tax rate.
[9] The reel frame id for this patent assignment is 4996/23.

4789690), titled as "Polyurethane Foam and Process for Its Preparation", was transferred from Dow Chemical Europe S.A. and Dow Chemical (Nederland) B.V. to the Dow Chemical Company on March 30, 1987. Since this type of transfer does not change the ownership status of a patent beyond a firm's boundary (i.e., the focal patent still belongs to the same organization) either, I manually check and remove them from my sample.

In addition to the USPTO Patent Assignment Dataset, I collect information on patent applications and grants, as well as patent-level statistics (e.g., backward and forward citations, number of patent claims, patent scope, among others), from the USPTO PatentsView Database. I collect patents' economic value from Noah Stoffman's website.[10] This dataset was originally constructed and used in Kogan et al. (2017), and it is extended to the year 2019 by the authors. I collect data on firms' fundamentals from Compustat and stock price information from CRSP. In terms of matching the USPTO patent data with Compustat firm records, I first standardize the name of USPTO corporate entities based on the name cleaning and standardization algorithm developed by the NBER Patent Data Project.[11] Next, I use the matching keys (based on standardized names obtained in the last step) to match the USPTO corporate entities with Compustat firm records. Finally, I manually check each entry to ensure the quality of my matching is good. I report the firm- and patent-level summary statistics in Table 2. Univariate firm comparisons and some descriptive statistics are given in Tables A1 and A2 of Appendix A of the Internet Appendix.

4.2 Construction of Key Variables

4.2.1 Innovation Productivity and Quality

Following the existing literature on corporate innovation, I use patent-based metrics to measure firm-level innovation productivity and innovation quality. I construct three different variables used as

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[10] See https://github.com/KPSS2017/Technological-Innovation-Resource-Allocation-and-Growth-Extended-Data.
[11] See https://sites.google.com/site/patentdataproject/Home/posts/namestandardizationroutinesuploaded.

proxies for a firm's innovation productivity. The first variable, *Num_Pat_3*, is the natural logarithm of 1 plus the number of patents filed by a firm in the last three years up to a given year. The second variable, *Num_Pat*, is the natural logarithm of 1 plus the number of patents filed by a firm in a given year. The third variable, *Num_Pat_Total*, is the natural logarithm of 1 plus the total number of patents filed by a firm up to a given year. I add 1 to the number of patents to avoid losing observations when a firm does not file any patent in a given year.

In addition, I construct three different variables used as proxies for a firm's innovation quality. The first variable, *Num_Cite_3*, is the natural logarithm of 1 plus the number of lifetime citations received by patents filed by a firm in the last three years up to a given year scaled by the number of patents filed by the firm in the last three years (i.e., number of citations per patent). The second variable, *Num_Cite*, is the natural logarithm of 1 plus the number of lifetime citations received by patents filed by a firm in a given year divided by the number of patents filed by the firm in that year. The third variable, *Num_Cite_Total*, is the natural logarithm of 1 plus the total number of lifetime citations received by all patents a firm files in a given year. Similarly, I add 1 to the number of citations to avoid losing any observation when a firm's patents do not receive any citations over their lifetime.

There are two types of truncation problems associated with patent data. The first problem is related to the patent count. A patent filed by a firm shows up in the USPTO patent dataset only after it is granted, and according to the data from USPTO, the average time lag between the filing and grant of a patent is two years. Therefore, toward the end of the sample period, the number of patents filed by a firm in a given year (or in the last three years) is likely to be reduced compared to earlier years of the sample period. The second problem is related to the number of citations received by a given patent. Patents filed and granted in earlier years of the sample period are expected to receive a larger number of citations than patents filed in later years. To mitigate these two types of truncation problems, I follow a similar methodology to that of Hall et al. (2001) and Seru (2014). Specifically, I scale a patent (number of citations received by a patent) by the total number of patents (citations received by all the patents) filed in the same year and technology class. I aggregate these class-adjusted measures to the firm level, which are then used in all the firm-level analyses. Throughout the empirical analysis I also include year fixed effects, which, to some extent, accounts for the trend of innovation across years.

4.2.2 Total Factor Productivity

I construct this firm-level measure following the methodology in Olley and Pakes (1996). This revenue-based measure is extensively used in other papers (e.g., see İmrohoroğlu and Tüzel (2014) and Kogan et al. (2017)). I begin by assuming a Cobb-Douglas production function of a firm:

$$y_{i,t} = \beta_0 + \beta_1 k_{i,t} + \beta_2 l_{i,t} + \omega_{i,t} + \eta_{i,t} \tag{1}$$

In this production function, $y_{i,t}$ is the log of the value added of firm i in year t. I use the total revenue of firm i in year t as a proxy. $k_{i,t}$ is the log of firm i's capital input, and $l_{i,t}$ is the log of firm i's labor input in year t. Following the existing literature, I use firm's capital expenditure as a proxy for capital input and employees' wage for labor input. $\omega_{i,t}$ is the (unobservable) log of firm i's total factor productivity (TFP) in year t. $\eta_{i,t}$ is the unobservable error term, and it could be either a measurement error or a unforecastable shock to productivity, according to Olley and Pakes (1996).

To estimate the set of parameters (β_0, β_1, β_2), I use the semi-parametric approach of Olley and Pakes (1996), since this approach accounts for the selection and simultaneity bias in the estimation process. The first step of the estimation process projects $y_{i,t}$ onto the space spanned by $l_{i,t}$ and the third order polynomial $\Phi_{i,t}$ (including a full set of interaction terms) of investment $I_{i,t}$ and capital expenditure $k_{i,t}$. Olley and Pakes (1996) approximate the polynomial $\Phi_{i,t}$ with fourth order, but my results are robust to different choices of the order of the polynomial. This step leads to the consistent estimate of β_2 in model (1), which accounts for the simultaneity bias.

The second step involves estimating the survival probability of a firm. I regress a survival indicator (which equals one if a firm survives from year t to t+1) on the third order polynomial $\Phi_{i,t}$

(including a full set of interaction terms) of investment $I_{i,t}$ and capital expenditure $k_{i,t}$ using a probit model, and I obtain the fitted values as the estimated probability (i.e., propensity score) of the firm i surviving from year t to t+1.

The third step of the estimation process involves estimating the following regression:

$$y_{i,t+1} - \hat{\beta}_2 l_{i,t+1} = \beta_1 k_{i,t+1} + g\big(P_{i,t}, \phi_{i,t} - \beta_0 - \beta_1 k_{i,t}\big) + \eta_{i,t+1} \tag{2}$$

I substitute β_2 on the left-hand side of model (2) with the estimated coefficient obtained from the first step of the estimation procedure. I substitute $P_{i,t}$ and $\Phi_{i,t}$ with corresponding fitted values from the second step of the estimation procedure. I estimate the coefficients β_0 and β_1 in model (2) using non-linear least squares to account for the possible non-linear nature of function g(·) in (2). Following Olley and Pakes (1996), by conditioning on the survival probability (propensity score), this approach also accounts for the selection problem that may arise in the estimation.

After I estimate the set of parameters (β_0, β_1, β_2), the (log) TFP of firm i in year t is obtained as follows:

$$\hat{\omega}_{i,t} = y_{i,t} - \hat{\beta}_0 - \hat{\beta}_1 k_{i,t} - \hat{\beta}_2 l_{i,t} \tag{3}$$

4.2.3 Technological Distance

This patent-level measure is constructed following the methodology suggested by Akcigit et al. (2016) and others. The technological distance of a patent captures the extent of how close the patent is to the owning firm's knowledge space (as represented by the firm's existing patent portfolio).

The construction of this measure consists of two steps. The first (and the most important) step is to figure out how close one technology class is to another by examining the citation pattern of these two classes. The closeness between patent technology class X and Y can be calculated using the following expression:

$$d(T_X, T_Y) \equiv 1 - \frac{\#(T_X \cap T_Y)}{\#(T_X \cup T_Y)} \tag{4}$$

The numerator $\#(T_X \cap T_Y)$ in the expression (4) represents the number of patents that cite patents in technology class X and Y simultaneously, while the denominator $\#(T_X \cup T_Y)$ represents the number of patents that cite patents in either technology class X or Y. This symmetric measure is intuitive: among all the patents that cite patents in either technology class X or Y, if the number of patents that simultaneously cite patents in technology class X and Y is larger, then it indicates that technology class X and Y is more proximate in the knowledge space. This in turn leads to the distance measure $d(T_X, T_Y)$ closer to zero. Therefore, the closer this measure $d(T_X, T_Y)$ is to zero, the more proximate the technology class X is to technology class Y.[12]

After I obtain the distance between every pair of technology class, the technological distance between a patent *p* and the owning firm's existing patent portfolio, $d_\iota(p, P_f)$, can be calculated as follows:

$$d_\iota(p, P_f) \equiv \left[\frac{1}{\|P_f\|}\sum_{p' \in P_f} d(T_p, T_{p'})^\iota\right]^{\frac{1}{\iota}} \tag{5}$$

Specifically, to calculate the technological distance of the focal patent p from the owning firm's existing patent portfolio P_f (i.e., portfolio of all the patents that had been invented prior to the focal patent p), I figure out the distance between technology class of patent *p* and that of every other patent *p'* in the patent portfolio P_f. Next I aggregate these individual technological distances into a single master variable according to (5). Here, $\| P_f \|$ denotes the number of patents in the firm's patent portfolio, and ι is set to 2/3 following the existing literature.[13] The larger this measure, the further away the focal patent is from the owning firm's knowledge space (as represented by its existing patent portfolio).

5. Determinants of Patent Transactions: Assignor Firms' Perspective

5.1 Firm-Level Determinants of Patent Transactions

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[12] Note that the distance between technology class X and itself is exactly zero.

[13] The results are robust to different values of ι (e.g., ι=1/3 or ι=1).

5.1.1 Innovation Productivity, Innovation Quality, and the Probability of Firms Selling Patents

I use the following firm-level baseline specification to test Hypothesis 1, where the unit of observation is firm-year.

$$I(Selling\ Patent_{i,t}) = \alpha_j + \alpha_t + \beta Innovation_{i,t} + X_{i,t-1}\gamma + u_{i,t} \tag{6}$$

In the specification (6), the dependent variable, $I(Selling\ Patent_{i,t})$, is a dummy variable equal to 1 if firm i sells some of its patens in year t. It is equal to 0 otherwise. The main right-hand side variable of interest is $Innovation_{i,t}$. It comprises two sets of variables that capture a firm's innovation capacity. The first set captures a firm's innovation productivity, which measures the amount of innovation output (i.e., patents) a firm produces within a certain period. In this paper I use three different variables as proxies for a firm's innovation productivity: $Num\_Pat\_3_{i,t}$, $Num\_Pat_{i,t}$, and $Num\_Pat\_Total_{i,t}$. The second set of variables captures a firm's innovation quality, which measures the quality of innovation output (i.e., patents) a firm produces within a certain period. I also use three different variables as proxies for a firm's innovation quality: $Num\_Cite\_3_{i,t}$, $Num\_Cite_{i,t}$, and $Num\_Cite\_Total_{i,t}$. The details on how to construct these variables are outlined in Section 4.2.1. $X_{i,t-1}$ represents a vector of firm-level lagged control variables, which includes total assets, R&D, ROA, leverage, current, cash, and capital expenditure. The details of how to construct these control variables are in Table 1. I also include 3-digit SIC industry (α_j) and year (α_t) fixed effects to absorb any industry-specific and time-varying factors that could affect a firm's decision to sell some of its patents. Standard errors are robust and clustered by firms. Tables 3 and 4 present the results related to this baseline specification.

Table 3 reports the relationship between a firm's innovation productivity and the probability of the firm selling some of its patents. Columns (1), (3), and (5) report the effect of innovation productivity on the probability of a firm selling some of its patents in a univariate regression. Columns (2), (4), and (6) report the effect in a multivariate framework. Overall, on average, a firm's innovation productivity has a positive and statistically significant effect (at 1% level) on the probability of the firm selling some of its patents, and this positive and significant effect is consistent with different proxies for a firm's innovation productivity. This effect is also economically significant. For example, one standard deviation increase in the (log) number of patents generated by a firm in the last three years is associated with an 8.8% increase in the probability of the firm selling some of its patents. This effect is approximately 1.8 times greater than the unconditional probability of a firm selling some of its patents (5.4%). This evidence suggests that firms with greater innovation productivity (as measured by the number of patents firms produce within a certain period) are more likely to sell some of their patents in the patent transactions.[14]

Table 4 presents the results on the relationship between a firm's innovation quality and the probability of it selling some of its patents. Columns (1), (3), and (5) of Table 4 report the effect of innovation quality on the probability of a firm selling some of its patents in a univariate regression, while Columns (2), (4), and (6) report such effect in a multivariate framework. Across different specifications, I document that a firm's innovation quality is positively associated with the probability of the firm selling some of its patents. This relationship is also statistically significant at 1% level and is consistent with different proxies for firm's innovation quality. This suggests that firms with higher innovation quality (as measured by higher citations per patent at the firm level) are more likely to sell some of their patents. Therefore, Tables 3 and 4 together confirm the predictions of Hypothesis 1.

5.1.2 Production Efficiency and the Probability of Firms Selling Patents

To test Hypothesis 2, I employ the following firm-level regression specification, where the unit of observation is firm-year.

$$I(Selling\ Patent_{i,t}) = \alpha_j + \alpha_t + \beta TFP_{i,t-1} + \delta Num\_Pat\_3_{i,t} +$$

[14] In Table A3 of Appendix B of the Internet Appendix, I conduct a robustness test using alternative measures of a firm's innovation productivity, where I scale $Num\_Pat\_3_{i,t}$, $Num\_Pat_{i,t}$, and $Num\_Pat\_Total_{i,t}$ by a firm's R&D ratio in year t. The results remain robust to different measures of innovation productivity.

$$\theta TFP_{i,t-1} \times Num\_Pat\_3_{i,t} + X_{i,t-1}\gamma + u_{i,t} \quad (7)$$

In this specification, the dependent variable is identical to that in specification (6). The main independent variable of interest is $TFP_{i,t-1}$, which is the firm i's Total Factor Productivity (TFP) in year t-1. Here I only use $Num\_Pat\_3_{i,t}$, which is the number of patents filed by firm i in the last three years up to year t, as the main proxy for a firm's innovation productivity, but the results are qualitatively similar when I use other proxies for firm's innovation productivity. A vector of firm-level lagged control variables is defined the same as in (6). 3-digit SIC industry (α_j) and year (α_t) fixed effects are included. Standard errors are robust and clustered by firms.

Table 5 reports the empirical results corresponding to the baseline specification (7). From Column (1) of Table 5 we can see that in a univariate regression, firm-level lagged TFP has a negative effect on the probability of a firm selling some of its patents. This negative and statistically significant coefficient suggests that firms with lower prior production efficiency are more likely to sell some of their patents in the subsequent year. This inference remains unchanged in Column (2) when I examine this relation in a multivariate framework. The magnitude of the effect of TFP on the probability of a firm selling some of its patents becomes larger, and the effect remains significant at 1% level. The effect of a firm's lagged TFP on the probability of it selling some of its patents is also economically significant: one standard deviation decrease in the TFP (0.859) is associated with a 4.4% increase in the probability of the firm selling patents, which translated into more than 80% of the unconditional probability. This evidence supports the first part of Hypothesis 2 that firms are more likely to sell some of their patents when their production efficiency is lower.

Next I include in the regression the interaction term of TFP and firm's innovation productivity, as proxied by the number of patents a firm generates in the past 3 years. The results are reported in Column (3) of Table 5. The coefficients on both the TFP and the interaction term are both negative and significant at 1% level. Together, this suggests that the effect of a firm's TFP on the probability of the firm selling its patents is negative, and this effect is stronger for firms with higher innovation productivity. If we evaluate the interaction term at the mean of *Num_Pat_3* (0.91), then the coefficient on the interaction term indicates that when a firm files the sample average number of patents in the last three years, one standard deviation decrease in the TFP is associated with a 1.3% increase in the probability of the firm selling patents, or 24% of the unconditional sample mean. This effect is also statistically significant at 1% level. The results and interpretations are very similar when I replace *Num_Pat_3* with *Num_Cite_3*, the number of citations per patent firms receive in the last 3 years. This is consistent with the prediction of the second part of Hypothesis 2. Overall, the results in Table 5 show that firms with lower production efficiency are more likely to sell some of their patents in the subsequent year, and this effect increases with firms' innovation quantity or quality.

5.2 Patent-Level Determinants of Patent Transactions

5.2.1 Patent's Technological Distance and the Probability of the Patent to be Sold

To test Hypothesis 3, I use the following patent-level regression specification, where the unit of observation is patent-filing-year.

$$I(Patent_{i,j,t}\ is\ sold) = \alpha_j \times \alpha_t + \beta Tech\_Dist_{i,j,t} + \delta Patent\_Num_{i,j,t} + \theta Tech\_Dist_{i,j,t} \times Patent\_Num_{i,j,t} + X_{i,t}\gamma + u_{i,t} \qquad (8)$$

The dependent variable in (8) is an indicator variable equal to 1 if patent i filed by firm j in year t is ever sold and equal to 0 otherwise. The main independent variable of interest is $Tech\_Dist_{i,j,t}$. It represents the technological distance of patent i filed in year t from the owning firm j's patent portfolio. $Patent\_Num_{i,j,t}$ denotes the number of patents in firm j's patent portfolio in year t when patent i is filed. I also include an interaction term to test the second part of Hypothesis 3. $X_{i,t}$ is a vector of patent-level control variables pertaining to patent i filed in year t. It includes number of forward citations, number of claims, patent scope, number of backward citations, and patent litigation dummy. The definition of these variables is in Table 1. In addition, owning firm (α_j) by filing-year (α_t) fixed effects are included, so that I am essentially comparing patents within the same firm that are filed in the same year. Standard errors are robust and clustered at the patent technology class level.

The empirical results associated with this specification are reported in Table 6. The positive and significant coefficient on the technological distance in Column (2) suggests that a patent with a greater distance to the owning firm's patent portfolio is more likely to be sold in a patent transaction. This is consistent with the prediction of the first part of Hypothesis 3. It suggests that a patent that is more likely to be a poor fit with the owning firm's operation is more likely to be reallocated to others. To test the second part of Hypothesis 3, I include in the regression the interaction term between technological distance and the size of a firm's patent portfolio. The results are reported in Column (3) of Table 6. The coefficient on the interaction term is positive and statistically significant at 1% level. This indicates that the technological distance of a patent is positively associated with the probability of the patent to be sold, and this effect is greater for firms with a larger number of patents in their portfolio. This result supports the prediction of the second part of Hypothesis 3. Overall, in terms of the patent-level determinant of patent transactions, I show that patents more distant from the seller firms' main operations are more likely to be sold in the patent transactions, and this effect increases with firms' innovation productivity.

5.2.2 Patent's Relative Technological Distance and the Probability of the Patent to be Sold

To test Hypothesis 4, I use the following patent-level regression specification, where the unit of observation is patent-filing-year.

$$I(Patent_{i,j,k,t}\ is\ sold) = \alpha_j + \alpha_k + \alpha_t + \beta Relative\_Tech\_Dist_{i,j,k,t} + X_{i,t}\gamma + u_{i,t} \tag{9}$$

The dependent variable in (9) is identical to the one in specification (8). Different from (8), the main independent variable of interest now becomes $Relative\_Tech\_Dist_{i,j,k,t}$. It is defined as the technological distance of patent i to the buyer firm k minus the technological distance of patent i to the seller firm

j. More negative this measure, technologically closer the patent i is to the buyer firm k than to the seller firm j. A vector of patent-level control variables $X_{i,t}$ pertaining to patent i filed in year t is defined identically to that in specification (8). It includes number of forward citations, number of claims, patent scope, number of backward citations, and patent litigation dummy. In addition, seller firm (α_j), buyer firm (α_k), and filing-year (α_t) fixed effects are included. Standard errors are robust and clustered at the patent technology class level.

Table 7 reports the results on the relationship between a patent's relative technological distance and the probability of it to be sold in a patent transaction. Column (1) reports the results in a univariate regression. The coefficient on the relative technological distance variable is negative and statistically significant at 1% level. This indicates that when a patent is technologically closer to a buyer firm than to a seller firm (i.e., this measure is negative), the patent is more likely to be sold in a patent transaction. In addition, the closer this patent is to the buyer firm than to the seller firm (i.e., the more negative this measure becomes), the more likely the patent is sold in a patent transaction. When I include a vector of patent-level control variables in Column (2), the implication remains unchanged. Together, these results support the prediction of Hypothesis 4.

In Table A4 of Appendix B of the Internet Appendix, I also examine the relationship between a patent's value and the probability of it to be sold in a patent transaction. $Eco\_Value_{i,j,t}$ represents the economic value of patent i filed in year t to the owning firm j. I obtain the economic value of patent i following the methodology of Kogan et al. (2017). Specifically, a patent's economic value is measured as the announcement return on the owning firm's stock during the time window around the grant of the patent. $Forward\_Citations_{i,t}$ is the truncation-adjusted number of forward citations received by patent i filed in year t. $X_{i,t}$ is defined exactly the same as in the specification (9). Owning firm (α_j) by filing-year (α_t) fixed effects are included. Standard errors are robust and clustered at the patent technology class level. The coefficient on either $Eco\_Value_{i,j,t}$ or $Forward\_Citations_{i,t}$ is positive and at least significant at 5% level. This suggests that a patent with a higher value (as measured by either economic value or scientific value) is more likely to be sold in a patent transaction.

6. Firm-Level Financial Consequences of Patent Transactions

6.1 Baseline Results

I utilize a matched-sample analysis to study the baseline financial consequences of patent transactions for seller firms. I match seller firms with all the non-seller firms in the same 3-digit SIC industry and transaction year. I then combine the seller and matched non-seller firms into different industry-year groups and stack all the groups to conduct the matched-sample analysis.[15]

I use the following specification to estimate a panel data of a three-year window around patent transactions. The unit of observation is firm-year.

$$Y_{i,j,t} = \alpha_j \times \alpha_t + \beta_1 Assignor_i \times Post_t + \beta_2 Assignor_i + X_{i,t}\gamma + u_{i,t} \tag{10}$$

The dependent variables include return on assets (ROA) and operating profitability of firm i in industry j in year t. ROA is constructed as a firm's earnings before interest (EBIT) in year t scaled by total assets, while operating profitability is constructed as a firm's operating income before depreciation in year t divided by total assets. $Assignor_i$ is a dummy variable equal to one if firm i is an assignor firm and equal to zero otherwise. $Post_t$ is a dummy variable that equals one if the observation is within three years after a patent transaction and equals zero otherwise. $X_{i,t}$ denotes a vector of firm-level controls, which include total assets, R&D, leverage, current, cash, and capital expenditure. I do not include $Post_t$ dummy in the regression, since it is subsumed by the industry-by-year fixed effects.

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[15] In Table A5 of Appendix B of the Internet Appendix, I report the results of a robustness test of the effect of patent transactions of operating performance using a matched sample of seller and non-seller firms based on the closest propensity score. I match each seller firm with one non-seller firm (with replacement) in the same 3-digit SIC industry and transaction year that has the closest propensity score, which is estimated based on the number of patents filed by a firm in the transaction year, total assets, R&D ratio, current year's ROA, leverage, current, cash, and capital expenditure. The results are qualitatively similar to my baseline results.

The standard errors are robust and clustered by firms. The main independent variable of interest is the interaction term $Assignor_i \times Post_t$.

Table 8 shows the results of the baseline estimation. In Column (1) where the dependent variable is ROA, the coefficient on the interaction estimator $Assignor_i \times Post_t$ is positive and statistically significant at 1% level. This indicates that in the three years following the patent transactions, the seller firms, on average, experience an increase in their ROA compared to non-seller firms. In Column (2) where the dependent variable is operating profitability, I also document a positive and statistically significant coefficient, suggesting that over the three years following the patent transactions, the seller firms, on average, have better operating profitability than non-seller firms. These results, taken together, implies that the seller firms experience an improvement in their operating performance (as measured by either ROA or operating profitability) after the patent transactions. The above findings are consistent with the prediction of Hypothesis 5A.[16]

6.2 Identification

In the baseline regressions, I establish that, compared to non-seller firms, seller firms experience an increase in their operating performance following the patent transactions. However, one could argue that the baseline results may suffer from several endogeneity biases. One such concern is the omitted variable bias. Even though I could control for different firms' fundamentals in the regression that arguably affect the firms' decision to sell patents, there could be unobservables that also affect such decisions. Therefore, to address this concern and establish the causality between patent transactions and operating performance, I utilize a DiD framework based on the American Inventors Protection Act of 1999 as a positive exogenous shock to the patent transaction incidence.

[16] To gain a better understanding of the sources of increase in ROA, I explore separately the effect of secondary market patent transactions on individual components of ROA, as well as its effect on firm-level total factor productivity (TFP). I use a similar specification as in (10) and report the results in Table A6. I find that seller firms increase their sales in the next three years subsequent to patent transactions. In addition, seller firms experience a decrease in their overhead costs and an increase in their cost of goods sold following the patent transactions. More importantly, I document seller firms also experience a significant improvement in their production efficiency as measured by the TFP following patent sales.

Enacted on November 29, 1999, this Act has one key part specifying that, upon its passage, patent applications filed in the U.S. are disclosed after 18 months, as opposed to when the patent is granted. This provision took effect in November 2020. The existing literature argues that this change results in faster knowledge diffusion.[17] After the passage of this Act, on average, a patent application is made available to the public sooner than before. I argue that this expedited publication process positively affect the patent transaction incidence in two ways. First, the Act makes it easier for the buyer firms to identify a potentially useful patent earlier. Second, the Act has facilitated a better knowledge spillover between firms and hence could potentially promote a better match between potential sellers and buyers. To empirically show that the passage of this Act has a positive effect on the patent transaction incidence, I regress the indicator variable of firms selling patents on the dummy $I(Year_t>2000)$, which is a year dummy equal to one if an observation is after the year 2000. I control for other factors that could affect a firm's decision to sell patents (as in my baseline specification of determinants of patent transactions). I include year trend in all the regressions to account for the potential trend in the firm's propensity to sell patents over time.[18] In addition, I also include industry or firm fixed effects for different specifications, and the standard errors are clustered at the firm level. The results are reported in Table A7 of Appendix B of the Internet Appendix. The positive and statistically significant coefficients on the dummy $I(Year_t>2000)$ across all the columns of Table A7 indicates that, after the year 2000, it is more likely for a firm to engage in a secondary market patent transaction. This seems to suggest that the Act could serve as a valid positive exogenous shock to the patent transaction incidence in my setting.

Therefore, to establish the causality between patent transactions and firms' operating performance, I estimate the following DiD framework using a panel data of a three-year window

[17] For example, Johnson and Popp (2003) find evidence that the passage of this Act expedites the patent publication disclosure and facilitates knowledge diffusion.
[18] In this particular table I do not include year fixed effects, since this would subsume my main independent variable of interest, $I(Year_t>2000)$.

around the year 2000, where the part of the Act related to patent application disclosure was in effect.

$$Y_{i,j,t} = \alpha_j \times \alpha_t + \beta_1 Assignor_i \times Post_t + \beta_2 Assignor_i + X_{i,t}\gamma + u_{i,t} \tag{11}$$

This regression specification is very similar to that in (10), but the difference is that now the $Post_t$ dummy is defined to be equal one if the observation is within three years after the year 2000. It is equal to zero otherwise. I include industry-by-year fixed effects so that I could compare firms within the same industry at every point in time.

The results associated with specification (11) are reported in Table 10. In Column (1) where the dependent variable is ROA, the coefficient on the DiD estimator *Assignor* × *Post* is positive and statistically significant at 1% level. This suggests that in the three years following the enactment of the American Inventor Protection Act, seller firms, on average, experience an improvement in their ROA compared to non-seller firms. The implication remains consistent when I change the dependent variable from ROA to operating profitability in Column (2).

One central assumption of the DiD estimation before we could establish causality of the results is the lack of pre-trend. Specific to my setting, there should be no clear pre-trend before the passage of this Act, so that the non-seller firms would serve as a valid counterfactual for seller firms if the Act had not been enacted. To empirically examine this assumption, I estimate the following regression.

$$Y_{i,j,t} = \alpha_j \times \alpha_t + \sum_{t=-3,\, t\neq -1}^{3} \beta_t Assignor_i \times Year_t + \delta Assignor_i + X_{i,t}\gamma + u_{i,j,t} \tag{12}$$

The dependent variables of this regression include ROA and operating profitability. $Year_t$ is a dummy variable equal to one if the year of an observation is t years away from the year 2000. It is equal to zero otherwise. I drop the year 1999 to avoid the collinearity problem and use it as the base group for comparison. Other variables are defined the same as those in specification (11).

The plots of coefficient β_t for two different outcome variables are given in Figures 3 and 4. The solid blue lines in both graphs represent the point estimates, and the red spike lines represent the 90% confidence interval of the coefficient estimates. From Figures 3 and 4, we can see that when the dependent variables are ROA or operating profitability, there are no clear pre-trends prior to the year 1999 (the point estimates are not statistically different from 0).

Further, to ensure the internal validity of my DiD estimator associated with the American Inventors Protection Act of 1999 documented in Table 10, I conduct a falsification test. The results are reported in Table A8 of Appendix B of the Internet Appendix. Specifically, I falsely assume that the part of the Act related to the expedited disclosure of patent applications was effective three years before it actually did (i.e., the year 2000). Therefore, based on the sample of all seller and non-seller firms, I estimate a three-year window around the year 1997 such that the panel ends before the actual year when the part of the Act related to patent application disclosure was in effect. The positive but insignificant coefficients on the DiD estimators in Table A8 for both dependent variables suggest that the results documented in Table 10 are likely to be driven by the Act itself instead of some alternative forces. Therefore, putting these pieces of evidence together, I argue that the positive relationship between secondary market patent transactions and seller firms' operating performance documented in the baseline analysis is likely causal.

6.3 Mechanism

This section discusses one of the potential underlying mechanisms that could drive the above results, which is seller firms increase their R&D focus following the patent transactions. To investigate the heterogenous treatment effect of patent transactions, I use a triple difference-in-differences model as follows.

$$Y_{i,j,t} = \alpha_j \times \alpha_t + \gamma Assignor_i \times Post_t \times Focus\_Increase_{i,t} + \beta_1 Assignor_i \times Post_t + \beta_2 Assignor_i \times Focus\_Increase_{i,t} + \beta_3 Post_t \times Focus\_Increase_{i,t} + \beta_4 Assignor_i + \beta_5 Focus\_Increase_{i,t} + X_{i,t}\gamma + u_{i,t} \tag{13}$$

The outcome variables, other right-hand side variables, and fixed effects are identical to those defined in (10). The new independent variable is $Focus\_Increase_{i,t}$. It is a dummy variable equal to one if the average technological distance of patents filed by firm i in the next 3 years is smaller than that of patents filed in year t. It is equal to zero otherwise. In other words, if firm i files patents that have a smaller technological distance on average in the next three years compared to year t, this means that the firm is conducting R&D activity closer to its main operations in the following years, and it hence represents an increase in its innovation focus. The coefficient on the triple interaction term, γ, identifies the difference between seller firms that increase focus after the patent transactions and those that do not. If the seller firms' increase in innovation focus is indeed the underlying channel driving the results, then I would expect to find the coefficient to be positive.

The results are reported in Table 11. For brevity, I only report the triple interaction term, $Assignor_i \times Post_t \times Focus\_Increase_{i,t}$, which is the main independent variable of interest, and the DiD estimator $Assignor_i \times Post_t$. The coefficient on this triple interaction term is positive and statistically significant at 5% level, while the coefficient on the DiD estimator is indistinguishable from zero. This indicates that the improvement in the seller firms' operating performance after the patent transactions is concentrated in the sub-sample where seller firms increase their innovation focus. It should also be noted that the magnitude of this coefficient is over three times as large as that in Table 8 for either of the two dependent variables (i.e., the baseline results of the consequences of patent transactions). This evidence suggests that the source of improvement in the operating performance mostly comes from seller firms which increase their R&D focus following the patent transactions.

I document some additional evidence further supporting this increase in innovation focus channel. First, I focus on the inventors' expertise and examine the technological similarity between patents of inventors and that of firms. I examine such relationship using the data on inventors obtained from the Harvard Patent Dataverse. This database contains the career trajectory of different inventors as well as their technology expertise (as shown by the patents filed by them).[19] I then construct the technological similarity measure as the cosine similarity between the technology classes of patents in the inventors' and firms' respective portfolios. Hence, this measure falls within the range of zero and one, and the closer this similarity measure is to one, the more similar an inventor's technology expertise is to the firm's own technology expertise. I report the results in Table 12.

In Panel A of Table 12, I examine the technological similarity between patents of firms and patents of inventors who are newly hired by firms in the next three years subsequent to year t. I find that the new inventors who flow into assignor firms in the first year after patent transactions have technology expertise that is more similar to the firms' own technology expertise, compared to new inventors hired by the same assignor firms during other periods. This is evidenced by the positive and significant coefficient on *I(Selling Patent)* in Column (1) of Panel A. In Panel B of Table 12, I also examine the technological similarity between firms' patents and patents of inventors who remain in the firms over the three years subsequent to year t. The positive and significant coefficients on *I(Selling Patent)* in Columns (1) to (3) of Panel B suggest that the inventors who remain in the assignor firms in the three years following patent transactions also share a more similar technological expertise with the firms.[20]

Second, I look at the seller firms' patenting activity following the patent transactions, which includes the number of patents generated by the seller firms and the average technological distance of these patents from the seller firms' patent portfolios. I report the results in Table 13. In Panel A of Table 13, I examine the innovation quantity produced by the seller firms subsequent to the patent transactions. The positive and significant coefficients across different columns suggest that seller firms

[19] The details of this dataset can be found in Li et al. (2014).

[20] It should be noted that assignor firms do not achieve the increase in their innovation focus simply by reducing the size of their R&D departments. In Table A9 of Appendix B of the Internet Appendix, I examine the inventors' flow of assignor firms following patent transactions. The positive and significant coefficients on I(Selling Patents) in all columns indicate that assignor firms experience an inflow of inventors over the three years subsequent to patent transactions.

generate a larger number of patents following the patent transactions, and the effect appears to be most pronounced in the first year following the patent transactions. In Panel B of Table 13 where dependent variables are now the average technological distance of new patents generated in different years to the seller firms' patent portfolios. The negative coefficients in all columns indicate that after the patent transactions, seller firms are creating patents that are closer to their main operations. Together, results in Tables 12 and 13 seem to support the increase in innovation focus channel.

7. Conclusion

In this paper, I analyze the secondary market for patents from the assignor firms' points of view. I study the determinants of assignor firms selling some of their patents and the implications of such transactions for the future financial performance of assignor firms. Overall, I document that at firm level, firms with higher innovation productivity (i.e., more able to innovate) but with lower production efficiency (i.e., less able to efficiently commercialize all of their patents) are more likely to sell some of their patents. At patent level, patents that are less relevant for seller firms' main operations are more likely to be sold in the patent transactions. In addition, patents that are technologically closer to buyer than to seller firms are more likely to be sold in the patent transactions, implying there are gains from trading the patents.

In terms of the economic and financial consequences of patent transactions, I document that seller firms experience a positive and statistically significant improvement in their operating performance in the three years after patent transactions. This improvement in the operating performance of seller firms is associated with an increase in their sales, a decrease in their overhead costs, and an increase in their TFP. Using the American Inventor Protection Act of 1999 as an exogenous shock to the patent transaction incidence, I show that the positive effect of secondary market patent transactions on seller firms' operating performance is causal. I find that the improvement in ROA and operating profitability is more pronounced in seller firms which increase their R&D focus after patent transactions, suggesting that an increase in innovation focus is an important channel driving the results. In addition, I find that inventors who are newly hired by assignor firms or those who choose to remain in assignor firms over the three years following patent transactions have similar technological expertise to the firms, and that seller firms generate more and technologically closer patents after the patent transactions. Together, these results further support the increase in innovation focus channel.

This paper also provides some research avenues for future study. For example, researchers could examine the determinants of patent transactions for private assignor firms and the implications of such transactions for these firms in terms of the likelihood of them receiving external financing (such as venture capital investments) and their future growth. Furthermore, policymakers could explore the economy- or market-wide factors that could remove the information frictions and facilitate the patent reallocations in the secondary market.

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Table 1: Variable Definitions

Panel A: Firm-level Variables	
Total Assets	Natural logarithm of firm i's book assets (compustat item: at) in a given year
Sales	Natural logarithm of firm i's total sales (compustat item: sale) in a given year
R&D	The ratio of firm i's R&D expense (compustat item: xrd) to its book assets (compustat item: at) in a given year
ROA	The ratio of firm i's EBIT (Earnings Before Interest) (compustat item: ebit) to its book assets (compustat item: at) in a given year
Leverage	Firm i's total debt (compustat item: dltt+dlc) scaled by its book assets (compustat item: at) in a given year
Current	Firm i's current assets (compustat item: act) divided by its current liabilities (compustat item: dlc) in a given year
Cash	Firm i's cash holdings (compustat item: che) divided by its book assets (compustat item: at) in a given year
CAPEX	Firm i's capital expenditure (compustat item: capx) scaled by book assets (compustat item: at) in a given year
Operating Profitability	Operating income before depreciation (compustat item: oibdp) of firm i in a given year divided by its book assets (compustat item: at)
COGS	Cost of goods sold (compustat item: cogs) of firm i in a given year divided by its book assets
SG&A	Selling, general and administrative expense (compustat item: xsga) of firm i in a given year divided by its book assets
Panel B: Patent-level Control Variables	
Forward Citations	The natural logarithm of the number of truncation-adjusted lifetime forward citation received by patent i
Claims	The natural logarithm of the number of claims in a patent's application
Patent Scope	The number of technology classes to which a patent belongs
Backward Citations	The natural logarithm of the number of backward citations of a patent filed in a given year
Litigation	A dummy variable equal to 1 if a patent is ever litigated and equal to 0 otherwise

Table 2: Summary Statistics

Panel A reports the summary statistics of firm-level variables. *I(Selling Patent)* is a dummy variable equal to 1 if a firm sells some of its patents in a given year and equal to 0 otherwise. *Num_Pat_3* is the natural logarithm of 1 plus the number of patents filed by a firm in the last three years up to a given year. *Num_Pat* is the natural logarithm of 1 plus the number of patents filed by a firm in a given year. *Num_Pat_Total* is the natural logarithm of 1 plus the total number of patents filed by a firm up to a given year. *Num_Cite_3* is the natural logarithm of 1 plus the number of lifetime citations per patents for patents filed by a firm in the last three years up to a given year. *Num_Cite* is the natural logarithm of 1 plus the number of lifetime citations per patent for patents filed by a firm in a given year. *Num_Cite_Total* is the natural logarithm of 1 plus the total number of lifetime citations received by all patents that a firm files in a given year. *TFP* is a firm's revenue-based total factor productivity in a given year, constructed following the methodology of Olley and Pakes (1996). *Total Assets* is the natural logarithm of a firm's book assets. *R&D* is the ratio of a firm's R&D expense to its book assets. *ROA* is measured as the ratio of a firm's EBIT (Earnings Before Interest) to its book assets. *Leverage* is the ratio of a firm's total debt to its book assets. *Current* is the ratio of a firm's current assets to its current liabilities. *Cash* is a firm's cash holdings divided by its book assets. *CAPEX* is the ratio of a firm's capital expenditure to its book assets. *Sales* is the natural logarithm of a firm's total sales. *COGS* is a firm's cost of goods sold divided by its book assets. *SG&A* is a firm's selling, general and administrative expense scaled by its book assets. Panel B reports the summary statistics of patent-level variables. *Tech_Dist* is the technological distance between a patent and the patent portfolio of the owning firm. *Forward Citations* is the natural logarithm of the number of truncation-adjusted lifetime forward citation received by a patent. *Claims* is the natural logarithm of the number of claims in a patent's application. *Patent Scope* is the number of technology classes to which a patent belongs. *Backward Citations* is the natural logarithm of the number of backward citations of a patent filed in a given year. *Litigation* is a dummy variable equal to 1 if a patent is ever litigated and equal to 0 otherwise.

Variable	Mean	Std. Dev.	1st Quartile	Median	3rd Quartile	Num. of Obs.
Panel A: Firm-level variables						
I(Selling Patent)	0.054	0.226	0	0	0	197,010
Num_Pat_3	0.912	1.509	0	0	1.386	197,010
Num_Pat	0.570	1.164	0	0	0.693	197,010
Num_Pat_Total	1.543	2.027	0	0.693	2.639	197,010
Num_Cite_3	0.001	0.004	0	0	0.001	197,010
Num_Cite	0.000	0.005	0	0	0.000	197,010
Num_Cite_Total	0.007	0.049	0	0	0.001	197,010

TFP	3.359	0.859	2.893	3.495	3.944	161,733
Total Assets	4.526	2.766	2.608	4.379	6.416	186,898
R&D	0.147	0.289	0.014	0.052	0.145	135,839
ROA	-0.197	0.930	-0.119	0.052	0.117	185,824
Leverage	0.309	0.556	0.031	0.194	0.367	186,348
Current	3.040	3.567	1.264	2.018	3.315	184,672
Cash	0.216	0.252	0.030	0.107	0.316	186,813
CAPEX	0.057	0.062	0.017	0.038	0.074	184,338
Sales	4.452	2.920	2.591	4.476	6.488	178,007
COGS	0.744	0.670	0.277	0.595	1.009	186,288
SG&A	0.514	0.845	0.165	0.301	0.522	164,622
Panel B: Patent-level variables						
I(Patent is Sold)	0.187	0.390	0	0	0	1,873,126
Tech_Dist	0.608	0.288	0.391	0.680	0.853	1,873,126
Forward Citations	0.001	0.007	0	0	0	1,873,126
Claims	2.684	0.655	2.303	2.833	3.045	1,873,126
Patent Scope	1.854	1.152	1	2	2	1,873,126
Backward Citations	2.080	1.012	1.386	2.079	2.639	1,873,126
Litigation	0.004	0.065	0	0	0	1,873,126

Table 3: Firm's Innovation Productivity and the Probability of the Firm Selling Patents

The dependent variable *I(Selling Patent)* is an indicator variable equal to 1 if firm i sells a patent in year t. It is equal to 0 otherwise. *Num_Pat_3* is the natural logarithm of 1 plus the number of patents generated by firm i in the last three years prior to year t. *Num_Pat_Total* is the natural logarithm of 1 plus the total number of patents in firm i's patent portfolio until year t. *Num_Pat* is the natural logarithm of 1 plus the number of patents generated by firm i in year t. Firm-level lagged control variables include *Total Assets*, calculated as the natural logarithm of firm i's book assets; *R&D*, calculated as the ratio of firm i's R&D expense to its book assets; *ROA*, measured as the ratio of firm's EBIT (Earnings Before Interest) to its book assets; *Leverage*, calculated as the ratio of firm i's total debt to its book assets; *Current*, calculated as the firm i's current assets divided by its current liabilities; *Cash*, calculated as the firm i's cash holdings divided by its book assets; and *CAPEX*, measured as the ratio of firm i's capital expenditure to its book assets. 3-digit SIC industry and year fixed effects are included. Robust standard errors are clustered by firms. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	I(Selling Patent)					
	(1)	(2)	(3)	(4)	(5)	(6)
Num_Pat_3	0.063***	0.058***				
	(0.002)	(0.002)				
Num_Pat_Total			0.049***	0.045***		
			(0.001)	(0.001)		
Num_Pat					0.08***	0.07***
					(0.002)	(0.002)
Total Assets		0.012***		0.012***		0.013***
		(0.001)		(0.001)		(0.001)
R&D		-0.004		-0.004		0.003
		(0.003)		(0.003)		(0.003)
ROA		-0.008***		-0.011***		-0.007***
		(0.001)		(0.001)		(0.001)
Leverage		0.004***		0.003***		0.004***
		(0.001)		(0.001)		(0.001)
Current		-0.002***		-0.002***		-0.001***
		(0.000)		(0.000)		(0.000)

Cash		-0.048***		-0.035***		-0.042***
		(0.005)		(0.005)		(0.005)
CAPEX		-0.139***		-0.084***		-0.143***
		(0.013)		(0.013)		(0.013)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.193	0.216	0.201	0.222	0.190	0.215
Num. of Obs.	197,010	122,183	197,010	122,183	197,010	122,183

Table 4: Firm's Innovation Quality and the Probability of the Firm Selling Patents

The dependent variable *I(Selling Patent)* is an indicator variable equal to 1 if firm i sells some of its patents in year t, and it is equal to 0 otherwise. *Num_Cite_3* is the natural logarithm of 1 plus the total number of lifetime citations received by firm i's patents filed in three years prior to year t divided by the total number of patents firm i filed in these three years. *Num_Cite* is the natural logarithm of 1 plus the total number of lifetime citations received by firm i's patents filed in year t divided by the total number of patents firm i filed in year t. *Num_Cite_Total* is the natural logarithm of 1 plus the total number of lifetime citations received by firm i's patents filed in year t. Firm-level lagged control variables include *Total Assets*, calculated as the natural logarithm of firm i's book assets; *R&D*, calculated as the ratio of firm i's R&D expense to its book assets; *ROA*, measured as the ratio of firm's EBIT (Earnings Before Interest) to its book assets; *Leverage*, calculated as the ratio of firm i's total debt to its book assets; *Current*, calculated as the firm i's current assets divided by its current liabilities; *Cash*, calculated as the firm i's cash holdings divided by its book assets; and *CAPEX*, measured as the ratio of firm i's capital expenditure to its book assets. 3-digit SIC industry and year fixed effects are included. Robust standard errors are clustered by firms. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	I(Selling Patent)					
	(1)	(2)	(3)	(4)	(5)	(6)
Num_Cite_3	1.651***	0.685**				
	(0.491)	(0.278)				
Num_Cite			1.495***	0.807***		
			(0.449)	(0.280)		
Num_Cite_Total					1.656***	1.214***
					(0.096)	(0.077)
Total Assets		0.039***		0.039***		0.030***
		(0.001)		(0.001)		(0.001)
R&D		0.029***		0.029***		0.024***
		(0.004)		(0.004)		(0.003)
ROA		-0.015***		-0.015***		-0.009***
		(0.001)		(0.001)		(0.001)
Leverage		0.004***		0.004***		0.004***
		(0.001)		(0.001)		(0.001)

Current		-0.002***		-0.002***		-0.002***
		(0.000)		(0.000)		(0.000)
Cash		-0.004		-0.004		-0.009*
		(0.005)		(0.005)		(0.005)
CAPEX		-0.084***		-0.084***		-0.101***
		(0.015)		(0.015)		(0.014)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.037	0.134	0.037	0.134	0.108	0.168
Num. of Obs.	197,010	122,183	197,010	122,183	197,010	122,183

Table 5: Firm-Level Production Efficiency and the Probability of the Firm Selling Patents

The dependent variable *I(Selling Patent)* is an indicator variable equal to 1 if firm i sells a patent in year t, and it is equal to 0 otherwise. *TFP* represents the firm i's revenue-based Total Factor Productivity (TFP) in year t-1. *Num_Pat_3* is the natural logarithm of 1 plus the number of patents filed by firm i in the last three years prior to year t. Firm-level lagged control variables include *Total Assets*, calculated as the natural logarithm of firm i's book assets; *R&D*, calculated as the ratio of firm i's R&D expense to its book assets; *ROA,* measured as the ratio of firm i's EBIT (Earnings Before Interest) to its book assets; *Leverage*, calculated as the ratio of firm i's total debt to its book assets; *Current*, calculated as the firm i's current assets divided by its current liabilities; *Cash*, calculated as the firm i's cash holdings divided by its book assets; and *CAPEX*, measured as the ratio of firm i's capital expenditure to its book assets. 3-digit SIC industry and year fixed effects are included. Robust standard errors are clustered by firms. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	I(Selling Patent)			
	(1)	(2)	(3)	(4)
TFP	-0.027***	-0.051***	-0.011***	-0.051***
	(0.003)	(0.003)	(0.001)	(0.003)
Num_Pat_3			0.106***	
			(0.005)	
Num_Cite_3				3.339***
				(1.451)
TFP × Num_Pat_3			-0.016***	
			(0.001)	
TFP × Num_Cite_3				-0.756***
				(0.377)
Total Assets		0.042***	0.011***	0.041***
		(0.001)	(0.001)	(0.001)
R&D		0.044***	0.002	0.045***
		(0.005)	(0.005)	(0.005)
ROA		-0.000	-0.000	-0.000
		(0.001)	(0.001)	(0.002)
Leverage		0.001	0.005***	0.001
		(0.002)	(0.002)	(0.002)
Current		-0.003***	-0.002***	-0.002***

		(0.000)	(0.000)	(0.000)
Cash		-0.015**	-0.049***	-0.016***
		(0.006)	(0.005)	(0.006)
CAPEX		-0.116***	-0.161***	-0.118***
		(0.017)	(0.015)	(0.017)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.050	0.157	0.233	0.155
Num. of Obs.	152,326	109,450	109,450	109,450

Table 6: Patent's Technological Distance to the Seller and the Probability of the Patent Being Sold in a Patent Transaction

The dependent variable, *I(Patent is Sold),* is an indicator variable equal to 1 if patent i filed in year t is sold by firm j, and it is equal to 0 otherwise. *Tech_Dist* is the technological distance between patent i filed in year t and the patent portfolio of owning firm j (i.e., all the patents held by firm j before patent i). *Patent_Num* is the number of patents in firm j's patent portfolio at the time of patent i's application in year t. Patent-level control variables includes *Forward Citations*, which is the natural logarithm of 1 plus the number of truncation-adjusted lifetime forward citation received by a patent; *Claims,* which is the natural logarithm of the number of claims in a patent's application; *Patent Scope,* which is the number of technology classes to which a patent belongs; *Backward Citations,* which is the natural logarithm of 1 plus the number of backward citations of a patent filed in a given year; and *Litigation,* which equals 1 if a patent is ever litigated and equals 0 otherwise. Owning firm by filing-year fixed effects are included. Robust standard errors are clustered at patent technology class level. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	I(Patent is Sold)		
	(1)	(2)	(3)
Tech_Dist	0.063***	0.066***	-0.071
	(0.014)	(0.014)	(0.057)
Patent_Num			0.055***
			(0.006)
Tech_Dist × Patent_Num			0.018**
			(0.009)
Forward Citations		-0.004	0.036
		(0.074)	(0.065)
Claims		0.004***	0.004***
		(0.001)	(0.001)
Patent Scope		-0.003**	-0.003**
		(0.001)	(0.002)
Backward Citations		0.004***	0.004***
		(0.001)	(0.001)
Litigation		0.129***	0.129***
		(0.014)	(0.014)

Firm × Filing Year FE	Yes	Yes	Yes
Adj. R^2	0.433	0.434	0.434
Num. of Obs.	1,859,106	1,859,106	1,859,106

Table 7: Patent's Relative Technological Distance to the Buyer versus the Seller and the Probability of the Patent Being Sold

The dependent variable *I(Patent is Sold)* is a dummy equal to 1 if patent i filed in year t is sold by seller firm j to buyer firm k and equal to 0 otherwise. *Relative_Tech_Dist* is the technological distance of patent i to the buyer firm k minus the technological distance of patent i to the seller firm j. Patent-level control variables include *Forward Citations*, the natural logarithm of the number of truncation-adjusted lifetime forward citation received by a patent; *Claims,* the natural logarithm of the number of claims in a patent's application; *Patent Scope,* the number of technology classes to which a patent belongs; *Backward Citations*, the natural logarithm of the number of backward citations of a patent filed in a given year; and *Litigation,* which equals 1 if a patent is ever litigated and equals 0 otherwise. Seller, buyer, and filing-year fixed effects are included. Robust standard errors are clustered at patent technology class level. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	I(Patent is Sold)	
	(1)	(2)
Relative_Tech_Dist	-0.082***	-0.052***
	(0.017)	(0.010)
Forward Citations		0.001
		(0.053)
Claims		0.000
		(0.001)
Patent Scope		-0.001
		(0.001)
Backward Citations		0.000
		(0.000)
Litigation		-0.004
		(0.003)
Seller Firm FE	Yes	Yes
Buyer Firm FE	Yes	Yes
Filing Year FE	Yes	Yes
Adj. R^2	0.454	0.492
Num. of Obs.	84,621	82,353

Table 8: Financial Consequences of Patent Transactions: Baseline Results

Return on Assets is defined as firm i's earnings before interest (EBIT) in year t divided by its book assets. *Operating Profitability* is defined as firm i's operating income before depreciation in year t divided by its book assets. *Assignor* is a dummy variable equal to 1 if firm i is the seller firm in a patent transaction. It is equal to 0 otherwise. *Post* is a dummy variable equal to 1 if the observation is within a three-year period after a patent transaction. It is equal to 0 otherwise. Firm-level control variables include *Total Assets*, calculated as the natural logarithm of firm i's book assets in year t; *R&D*, calculated as the ratio of firm i's R&D expense to its book assets in year t; *Leverage*, calculated as the ratio of firm i's total debt to its book assets in year t; *Current*, calculated as the firm i's current assets divided by its current liabilities in year t; *Cash*, calculated as the firm i's cash holdings divided by its book assets in year t; and *CAPEX*, measured as the ratio of firm i's capital expenditure to its book assets in year t. Industry-by-year fixed effects are included in both regressions. Robust standard errors are clustered by firms. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	Return on Assets	Operating Profitability
	(1)	(2)
Assignor × Post	0.034***	0.032***
	(0.006)	(0.007)
Assignor	-0.076***	-0.069***
	(0.008)	(0.008)
Firm-level Controls	Yes	Yes
Industry × Year FE	Yes	Yes
Adj. R^2	0.581	0.580
Num. of Obs.	134,844	134,955

Table 10: Diff-in-Diff Analysis: The Impact of American Inventors Protection Act

Return on Assets is defined as firm i's earnings before interest (EBIT) in year t divided by its book assets. *Operating Profitability* is defined as firm i's operating income before depreciation in year t divided by its book assets. *Assignor* is a dummy variable equal to 1 if a firm is a seller firm in a patent transaction. It is equal to 0 otherwise. *Post* is a dummy variable equal to 1 if the unit of observation is within a three-year period after the year 2000. It is equal to 0 otherwise. Firm-level control variables include *Total Assets*, calculated as the natural logarithm of firm i's book assets in year t; *R&D*, calculated as the ratio of firm i's R&D expense to its book assets in year t; *Leverage*, calculated as the ratio of firm i's total debt to its book assets in year t; *Current*, calculated as the firm i's current assets divided by its current liabilities in year t; *Cash*, calculated as the firm i's cash holdings divided by its book assets in year t; and *CAPEX*, measured as the ratio of firm i's capital expenditure to its book assets in year t. Industry-by-year fixed effects are included in both regressions. Robust standard errors are clustered by firms. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	Return on Assets	Operating Profitability
	(1)	(2)
Assignor × Post	0.044^{***}	0.046^{***}
	(0.015)	(0.014)
Assignor	-0.040^{***}	-0.038^{***}
	(0.013)	(0.012)
Firm-level Controls	Yes	Yes
Industry × Year FE	Yes	Yes
Adj. R^2	0.540	0.533
Num. of Obs.	36,709	36,617

Table 11: Triple Diff-in-Diff Analysis and Assignor Firms' Increase in Focus

Return on Assets is defined as firm i's earnings before interest (EBIT) in year t divided by its book assets. *Operating Profitability* is defined as firm i's operating income before depreciation in year t divided by its book assets. *Assignor* is a dummy variable equal to 1 if firm i is the seller firm in a patent transaction. It is equal to 0 otherwise. *Post* is a dummy variable equal to 1 if the observation is within a three-year period after a patent transaction. It is equal to 0 otherwise. *Focus_Increase* is a dummy variable equal to 1 if the average technological distance of patents filed by firm i in the next three years is smaller than that of patents filed in year t; it is equal to 0 otherwise. Firm-level control variables include *Total Assets*, calculated as the natural logarithm of firm i's book assets in year t; *R&D*, calculated as the ratio of firm i's R&D expense to its book assets in year t; *Leverage*, calculated as the firm i's total debt scaled by its book assets in year t; *Current*, calculated as the firm i's current assets divided by its current liabilities in year t; *Cash*, calculated as the firm i's cash holdings scaled by its book assets in year t; and *CAPEX*, measured as the ratio of firm i's capital expenditure to its book assets in year t. Industry-by-year fixed effects are included. Robust standard errors are clustered by firms. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	Return on Assets	Operating Profitability
	(1)	(2)
Assignor × Post × Focus_Increase	0.048**	0.045**
	(0.021)	(0.021)
Assignor × Post	0.028***	0.027***
	(0.008)	(0.008)
Other Triple DiD Terms	Yes	Yes
Firm-level Controls	Yes	Yes
Industry × Year FE	Yes	Yes
Adj. R^2	0.581	0.580
Num. of Obs.	134,844	134,955

Table 12: Technological Similarity Between Inventors and Assignor Firms Following Patent Transactions

$Tech\_Similarity_{t+1}$ is the technological similarity between patents of inventors who are newly hired by firm i in year t+1 (Panel A), or patents of inventors who remain in firm i in year t+1 (Panel B), and firm i's patents up to year t+1. It is calculated as the cosine similarity between technology classes of patents in inventors' and firms' respective portfolios. *$Tech\_Similarity_{t+2}$* and *$Tech\_Similarity_{t+3}$* are defined similarly. *I(Selling Patent)* is a dummy equal to 1 if firm i sells some of its patents in year t. Firm-level control variables include *Total Assets*, the natural logarithm of firm i's book assets in year t; *R&D*, the ratio of firm i's R&D expense to its book assets in year t; *ROA*, the ratio of a firm's EBIT to its book assets; *Leverage*, the firm i's total debt scaled by its book assets in year t; *Current*, the firm i's current assets divided by its current liabilities in year t; *Cash*, the firm i's cash holdings scaled by its book assets in year t; and *CAPEX*, the ratio of firm i's capital expenditure to its book assets in year t. Firm and year fixed effects are included in both panels. Robust standard errors are clustered by firms. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

Panel A: New Inventors			
	$Tech\_Similarity_{t+1}$	$Tech\_Similarity_{t+2}$	$Tech\_Similarity_{t+3}$
	(1)	(2)	(3)
I(Selling Patent)	0.020**	-0.001	-0.003
	(0.008)	(0.008)	(0.009)
Firm-level Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Adj. R^2	0.365	0.363	0.362
Num. of Obs.	7,634	7,208	6,737
Panel B: Remaining Inventors			
	$Tech\_Similarity_{t+1}$	$Tech\_Similarity_{t+2}$	$Tech\_Similarity_{t+3}$
	(1)	(2)	(3)
I(Selling Patent)	0.008*	0.017***	0.020***
	(0.004)	(0.005)	(0.005)
Firm-level Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Adj. R^2	0.502	0.502	0.502
Num. of Obs.	25,494	23,491	21,549

Table 13: Seller Firms' Patenting Activity Following Patent Transactions

Num_Pat_{t+1} is the natural logarithm of 1 plus the number of patents generated by firm i in year t+1. *Avg_Dist_{t+1}* is the average technological distance of all patents filed by firm i in year t+1. The remaining dependent variables are defined similarly. Firm-level control variables include *Total Assets*, calculated as the natural logarithm of firm i's book assets; *R&D*, calculated as the ratio of firm i's R&D expense to its book assets; *ROA*, measured as the ratio of firm's EBIT (Earnings Before Interest) to its book assets; *Leverage*, calculated as the ratio of firm i's total debt to its book assets; *Current*, calculated as the firm i's current assets divided by its current liabilities; *Cash*, calculated as the firm i's cash holdings divided by its book assets; and *CAPEX*, measured as the ratio of firm i's capital expenditure to its book assets. Firm and year fixed effects are included. Robust standard errors are clustered by firms. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

Panel A: Innovation Quantity			
	Num_Pat_{t+1}	Num_Pat_{t+2}	Num_Pat_{t+3}
	(1)	(2)	(3)
I(Selling Patent)	0.161***	0.071***	0.029*
	(0.017)	(0.017)	(0.017)
Firm-level Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Adj. R^2	0.794	0.798	0.803
Num. of Obs.	166,301	152,509	139,570
Panel B: Technological Distance of Patents			
	Avg_Dist_{t+1}	Avg_Dist_{t+2}	Avg_Dist_{t+3}
	(1)	(2)	(3)
I(Selling Patent)	-0.008***	-0.006**	-0.007**
	(0.003)	(0.003)	(0.003)
Firm-level Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Adj. R^2	0.608	0.619	0.625
Num. of Obs.	50,254	46,796	43,477

Figure 1: Number and Percentage of Firms Selling Patents (1980-2017)

This figure shows the number and percentage of innovative firms (including both private and public firms) selling their patents in the secondary market from 1980 to 2017. The data is from the USPTO Patent Reassignment Database.

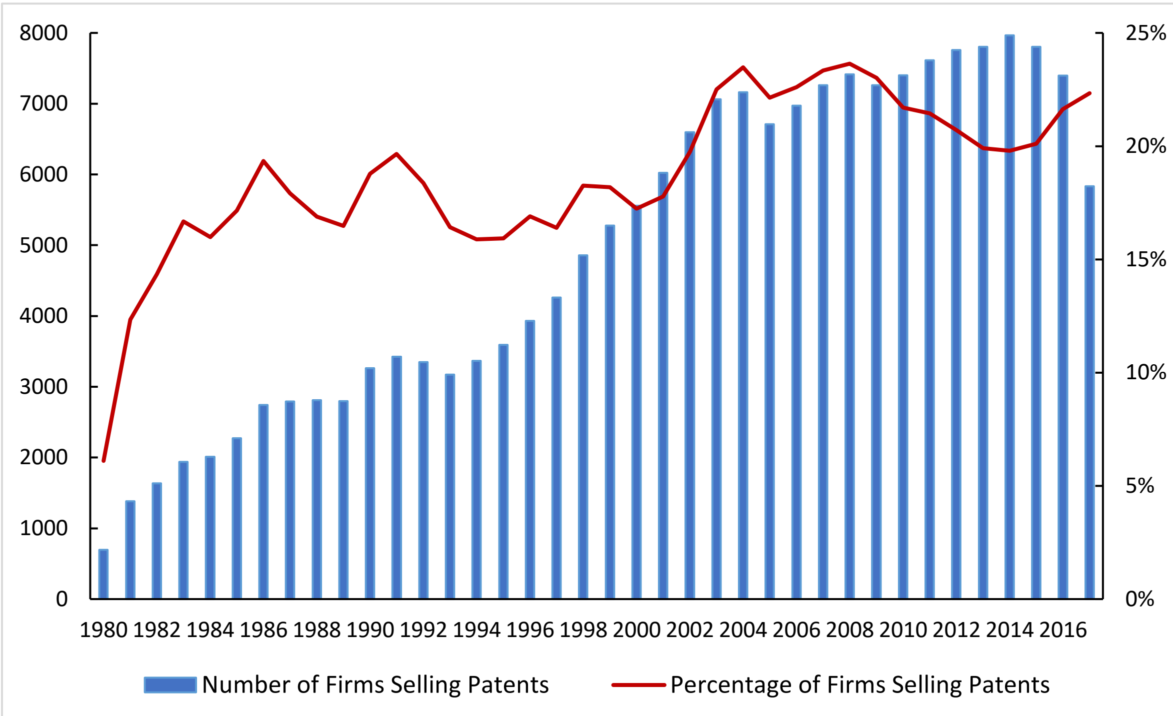


Figure 2: Number of Patents Sold (1980-2017)

This figure shows the number of patents sold in the U.S. patent secondary market from 1980 to 2017. Data is from the USPTO Patent Reassignment Database. This figure only shows the patents sold in secondary market transactions and does not include the change of ownership of patents due to other reasons (mergers & acquisitions, mortgage, security interest etc.).

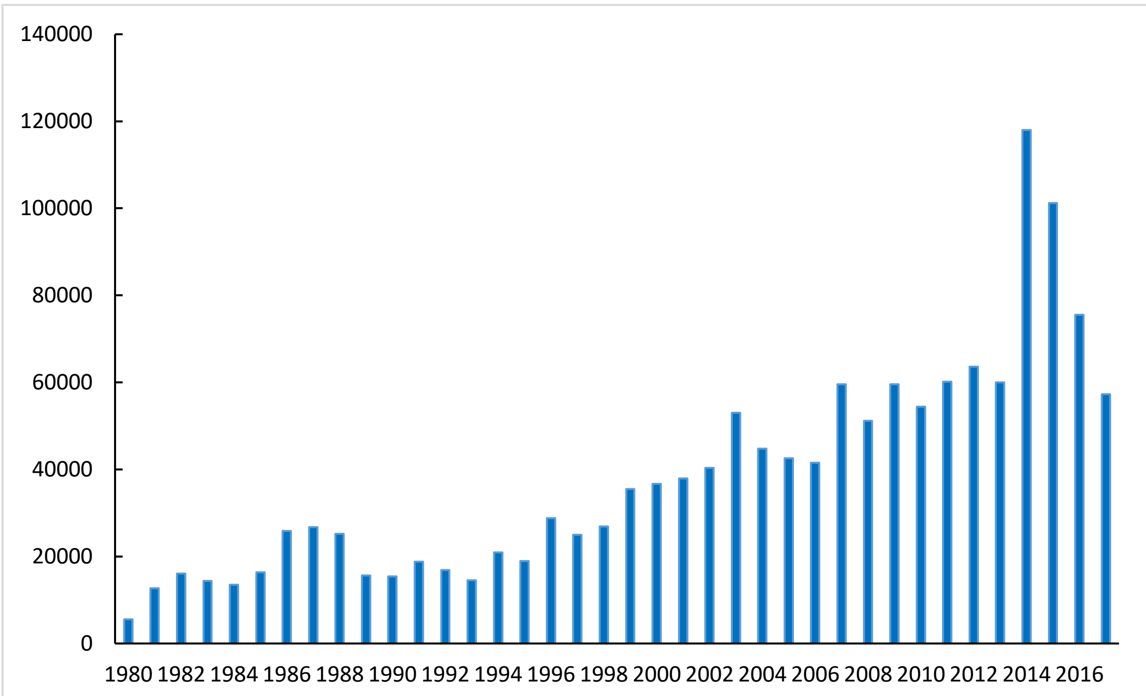


Figure 3: Coefficients Dynamics Around American Inventors Protection Act: The Case of Return on Assets

This figure plots the dynamics of coefficient on the DiD estimator *Assignor$_i$* × *Year$_t$* in the regression specification (12). The dependent variable here is $ROA_{i,j,t}$, constructed as EBIT of firm i in industry j in year t divided by its book assets. A vector of firm-level control variables includes: *Total Assets,* calculated as logarithm of firm i's book assets in year t; *R&D*, calculated as the ratio of firm i's R&D expense to its book assets in year t; *Leverage*, calculated as the ratio of firm i's total debt to its book assets in year t; *Current Ratio*, calculated as the firm i's current assets divided by its current liabilities in year t; *Cash*, calculated as the firm i's cash holdings divided by its book assets in year t; and *CAPEX*, measured as the ratio of firm i's capital expenditure to its book assets in year t. Industry-by-year fixed effects are included. Robust standard errors are clustered by firms.

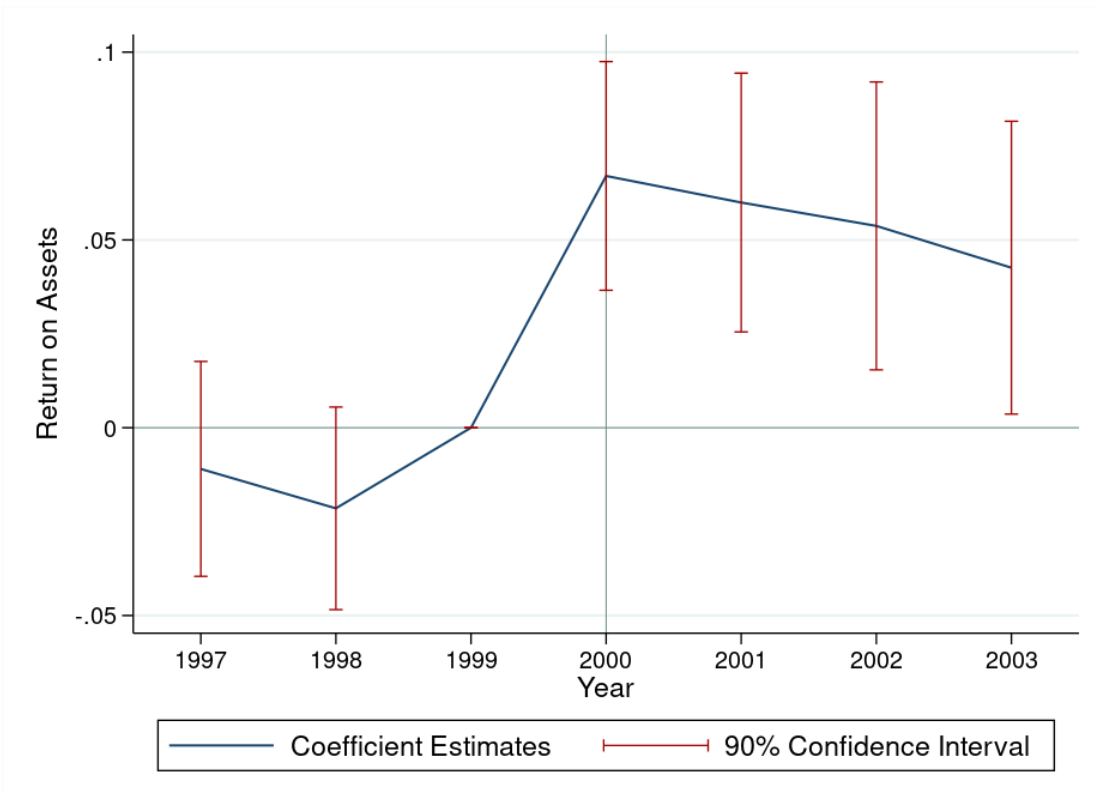
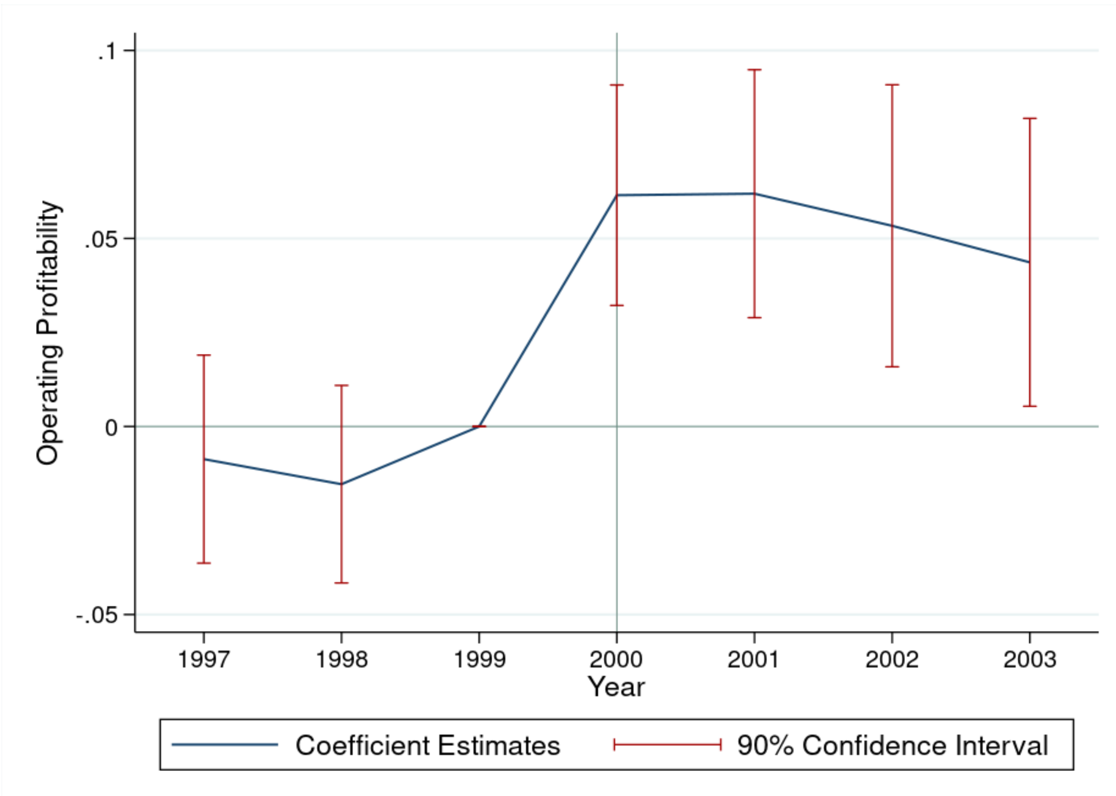


Figure 4: Coefficients Dynamics Around American Inventors Protection Act: The Case of Operating Profitability

This figure plots the dynamics of coefficient on the DiD estimator *Assignor*$_i$ × *Year*$_t$ in the regression specification (12). The dependent variable here is *Operating Profitability*$_{i,j,t}$, constructed as the operating income of firm i in industry j in year t scaled by its book assets. A vector of firm-level control variables includes: *Total Assets,* calculated as logarithm of firm i's book assets in year t; *R&D*, calculated as the ratio of firm i's R&D expense to its book assets in year t; *Leverage*, calculated as the ratio of firm i's total debt to its book assets in year t; *Current Ratio*, calculated as the firm i's current assets divided by its current liabilities in year t; *Cash*, calculated as the firm i's cash holdings divided by its book assets in year t; and *CAPEX*, measured as the ratio of firm i's capital expenditure to its book assets in year t. Industry-by-year fixed effects are included. Robust standard errors are clustered by firms.



Internet Appendix for "Why Do Innovative Firms Sell Patents? An Empirical Analysis of the Causes and Consequences of Secondary Market Patent Transactions"

Appendix A: Descriptive Statistics

This section reports the univariate firm comparison between assignor and non-assignor firms and some descriptive statistics. Table A1 reports the univariate firm comparison. On average, assignor firms have higher innovation productivity than non-assignor firms. For example, assignor firms generate approximately 25 patents per year on average. As a comparison, non-assignor firms only file 0.6 patents per year. This difference is statistically significant at 1% level. Assignor firms also have a higher innovation quality than non-assignor firms, as measured by different citation-based variables used as the proxy for innovation quality. For example, assignor firms on average receive 20.9 citations per patent for all the patents they have filed in the last three years, while this number for non-assignor firms is only 5.39. In addition, assignor firms are also larger (in terms of total assets) and spend more (in absolute terms) in R&D than non-assignor firms. However, the average R&D ratio of assignor firms is lower than that of non-assignor firms, presumably because of the larger size of assignor firms. These two types of firms do not differ much in leverage, short-term liquidity (as measured by the current ratio), and investment opportunities (as measured by capital expenditure).

Table A2 gives some descriptive statistics about the industry distribution of assignor firms and the technology class distribution of patents sold in the patent transactions. Panel A of Table A2 reports the 3-digit SIC industry classification of assignor firms. During the sample period from 1980 to 2017, among all assignor firms, the top five industries to which the assignor firms belong are Drugs (12.11%), Computer Programming and Data Processing Services (9.13%), Medical Instruments and

Supplies (7.19%), Electronic Components and Accessories (5.47%), and Computer and Office Equipment (5.11%). Most of these five industries are R&D intensive. Panel B of Table A2 reports the NBER technology category of patents sold on the secondary market. The top three technology categories are Computer & Communications, Electrical & Electronic, and Chemical. It is interesting to note that, although firms in the drugs industry account for a large part of the assignor firm sample, the number of patents in drugs and chemical category that are traded on the secondary market is relatively small, compared to patents in other NBER technology categories.

Table A1: Univariate Firm Comparison

Number of Patents in Last 3 Years is the number count of patents filed by a firm in the last 3 years up to a given year. *Number of Patents Per Year* is the number count of patents filed by a firm in a given year. *Total Number of Patents* is the total number count of patents filed by a firm up to a given year. *Number of Citations Per Patent in Last 3 Years* is the number of lifetime citations per patents for patents filed by a firm in the last 3 years up to a given year. *Number of Citations Per Patent* is the number of lifetime citations per patent for patents filed by a firm in a given year. *Total Number of Citations* is the total number of lifetime citations received by all patents filed by a firm in a given year. *Total Assets* is a firm's total book assets. *R&D Expense* is a firm's R&D expense in a given year. *R&D* is the ratio of a firm's R&D expense to its book assets. *ROA* is measured as the ratio of a firm's EBIT (Earnings Before Interest) to its book assets. *Leverage* is the ratio of a firm's total debt to its book assets. *Current* is the ratio of a firm's current assets to its current liabilities. *Cash* is measured as a firm's cash holdings divided by its book assets. *CAPEX* is the ratio of a firm's capital expenditure to its book assets. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

Variable	Assignors	Non-assignors	Difference
Number of Patents in Last 3 Years	73.34	1.56	71.78***
Number of Patents Per Year	24.84	0.55	24.29***
Total Number of Patents	422.64	5.80	416.84***
Number of Citations Per Patent in Last 3 Years	20.90	5.39	15.51***
Number of Citations Per Patent	14.27	2.79	11.48***
Total Number of Citations	379.91	10.31	369.60***
Total Assets	4727.10	1732.77	2994.33***
R&D Expense	163.20	25.86	137.35***
R&D	0.15	0.39	-0.24***
ROA	0.06	-0.01	0.07***
Leverage	0.49	0.49	0.00
Current	3.52	3.54	-0.02
Cash	0.20	0.23	-0.03***
CAPEX	0.06	0.06	0.00*
Num. of Obs.	4,842	9,635	

Table A2: Industry and Technology Class Distribution

Panel A: 3-digit SIC Industry Classification of Assignors		
3-Digit SIC Industry	Frequency	Percent
Drugs	593	12.11%
Computer Programming and Data Processing Services	447	9.13%
Medical Instruments and Supplies	352	7.19%
Electronic Components and Accessories	268	5.47%
Computer and Office Equipment	250	5.11%
Communications Equipment	177	3.62%
Measuring and Controlling Devices	174	3.55%
Motor Vehicles and Equipment	111	2.27%
Special Industry Machinery	87	1.78%
General Industrial Machinery	73	1.49%
Construction and Related Machinery	61	1.25%
Refrigeration and Service Machinery	50	1.02%
Toys and Sporting Goods	50	1.02%
Panel B: The NBER Technology Category of the Patents Sold		
NBER Technology Category	Number	Percent
Computers & Communications	216,715	42.72%
Electrical & Electronic	108,385	21.36%
Chemical	62,068	12.23%
Mechanical	48,648	9.59%
Drugs & Medical	30,782	6.07%

Appendix B: Additional Results

This section reports several additional results. I first conduct a robustness test of examining the relationship between a firm's innovation productivity and the probability of the firm selling some of its patents. Different from Table 3, I use alternative measures as proxies for a firm's innovation productivity. In Table A3, the main independent variables are *Num_Pat_3/R&D,* which is the natural logarithm of 1 plus the number of patents generated by firm i in the last three years prior to year t scaled by firm i's R&D ratio in year t. *Num_Pat_Total/R&D,* which is the natural logarithm of 1 plus the total number of patents in firm i's patent portfolio until year t scaled by firm i's R&D ratio in year t. *Num_Pat/R&D,* which is the natural logarithm of 1 plus the number of patents generated by firm i in year t scaled by firm i's R&D ratio in year t.

I then explore the relationship between a patent's value (as represented by its scientific value or its economic value) and the probability of it to be sold in a secondary market patent transaction. The corresponding results are reported in Table A4. The economic value of a patent is measured as the announcement return on owning firm's stock around the grant of the patent (following the methodology of Kogan et al. (2017)). The scientific value of a patent is constructed as the number of forward citations (truncation-adjusted) received by the patent. I show that a patent with higher economic value or higher scientific value is more likely to be sold in a secondary market patent transaction.

I conduct a robustness test of the effect of patent transactions on firms' subsequent operating performance using a matched sample of seller and non-seller firms based on the closest propensity score. For each seller firm, I select one non-seller firm (with replacement) in the same 3-digit SIC industry and transaction year that has the closest propensity score estimated using the number of patents filed by a firm in the transaction year, total assets, R&D ratio, current year's ROA, leverage, current, cash, and capital expenditure. I combine a seller firm and the matched non-seller firm into a cohort, and I then stack all the cohorts of seller and matched non-seller firms to conduct DiD analysis. The results documented in Table A5 are broadly consistent with the empirical patterns shown in Table 8. Overall, compared to non-seller firms that are at least similar in terms of observables, seller firms experience an increase in operating performance (as measured by ROA and operating profitability) following patent transactions.

To delve deeper and gain a better understanding of the sources of increase in ROA, I explore separately the effect of secondary market patent transactions on individual components of ROA, as well as its effect on firm-level total factor productivity (TFP). I use a similar specification as in (10) and report the results in Table A6. I find that seller firms increase their sales in the next three years subsequent to patent transactions. In addition, seller firms experience a decrease in their overhead costs and an increase in their cost of goods sold following the patent transactions. More importantly, I document seller firms also experience a significant improvement in their production efficiency as measured by the TFP following patent sales.

Table A7 reports the results on the validity of American Inventors Protection Act of 1999 used as an exogenous shock to the patent transaction incidence in my setting. In this table, the main independent variable is *I(Year > 2000)*, which is a dummy variable equal to 1 if an observation is after the year 2000, the year in which the patent disclosure requirement is effective. The coefficient on this variable is positive and significant across different specifications, suggesting that following the passage of this Act, assignor firms are more likely to engage in secondary market patent transactions.

In Table A8, to ensure the internal validity of my DiD estimator associated with the American Inventors Protection Act of 1999 documented in Table 10, I conduct a falsification test. Specifically, I falsely assume that the part of the Act related to the expedited disclosure of patent applications was effective three years before it actually did (i.e., the year 2000). Therefore, based on the sample of all assignor and non-assignor firms, I estimate a three-year window around the year 1997 such that the panel ends before the actual year when the part of the Act related to patent application disclosure was in effect. The positive but insignificant coefficients on the DiD estimators suggest that the results documented in Table 10 are likely to be driven by the Act itself instead of some alternative forces.

I examine the inventors' flow of assignor firms in the three years subsequent to patent transactions in Table A9. I find that assignor firms do not achieve the increase in their innovation focus simply by reducing the size of their R&D departments. The positive and statistically significant coefficients on *I(Selling Patent)* in all the columns of Table A9 suggest that assignor firms experience an inflow of inventors over the next three years after patent transactions.

Table A3: Firm's Innovation Productivity and the Probability of the Firm Selling Patents: Robustness Test

This table reports the robustness test of the relationship between a firm's innovation productivity and the probability of the firm selling some of its patents. The dependent variable *I(Selling Patent)* is an indicator variable equal to 1 if firm i sells a patent in year t. It is equal to 0 otherwise. *Num_Pat_3/R&D* is the natural logarithm of 1 plus the number of patents generated by firm i in the last three years prior to year t, scaled by firm i's R&D ratio in year t. *Num_Pat_Total/R&D* is the natural logarithm of 1 plus the total number of patents in firm i's patent portfolio until year t, scaled by firm i's R&D ratio in year t. *Num_Pat/R&D* is the natural logarithm of 1 plus the number of patents generated by firm i in year t, scaled by firm i's R&D ratio in year t. Firm-level lagged control variables include *Total Assets*, calculated as logarithm of firm i's book assets; *R&D*, calculated as the ratio of firm i's R&D expense to its book assets; *ROA* is measured as the ratio of firm's EBIT (Earnings Before Interest) to its book assets; *Leverage*, calculated as the ratio of firm i's total debt to its book assets; *Current*, calculated as the firm i's current assets divided by its current liabilities; *Cash*, calculated as the firm i's cash holdings divided by its book assets; and *CAPEX*, measured as the ratio of firm i's capital expenditure to its book assets. 3-digit SIC industry and year fixed effects are included. Standard errors are robust and clustered by firms. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	I(Selling Patent)					
	(1)	(2)	(3)	(4)	(5)	(6)
Num_Pat_3/R&D	0.00005***	0.00002***				
	(0.00001)	(0.00000)				
Num_Pat_Total/R&D			0.00002***	0.00000***		
			(0.00000)	(0.00000)		
Num_Pat/R&D					0.00008***	0.00004***
					(0.00002)	(0.00001)
Total Assets		0.041***		0.041***		0.040***
		(0.002)		(0.002)		(0.002)
R&D		0.038***		0.038***		0.037***
		(0.004)		(0.004)		(0.004)
ROA		-0.014***		-0.015***		-0.014***
		(0.002)		(0.002)		(0.002)

Leverage		0.003*		0.003*		0.003*
		(0.002)		(0.002)		(0.002)
Current		-0.002***		-0.002***		-0.002***
		(0.000)		(0.000)		(0.000)
Cash		-0.008		-0.008		-0.008
		(0.006)		(0.006)		(0.006)
CAPEX		-0.087***		-0.087***		-0.087***
		(0.016)		(0.017)		(0.016)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.051	0.140	0.047	0.139	0. 052	0.141
Num. of Obs.	128,162	112,511	128,162	112,511	128,162	112,511

Table A4: Patent's Value and the Probability of a Patent Sold

I(Patent is Sold) is an indicator variable equal to 1 if patent i filed in year t is sold by firm j. *Eco_Value* is the economic value of patent i to the owning firm j filed in year t, measured as the stock return on firm j upon grant of patent i. *Forward Citations* is the natural logarithm of the truncation-adjusted total number of forward lifetime citations received by patent i filed in year t. Patent-level control variables includes *Claims,* the natural logarithm of the number of claims in a patent's application; *Patent Scope,* measured as the number of technology classes to which a patent belongs; *Backward Citations,* the natural logarithm of the number of backward citations of a patent filed in a given year; and *Litigation,* which equals 1 if a patent is ever litigated and equals 0 otherwise. Owning firm by filing-year fixed effects are included. Robust standard errors are clustered at patent technology class level. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	I(Patent is Sold)		
	(1)	(2)	(3)
Eco_Value	0.004**		0.004**
	(0.002)		(0.002)
Forward Citations		0.181***	0.180***
		(0.061)	(0.061)
Claims	0.004***	0.004***	0.004***
	(0.001)	(0.001)	(0.001)
Patent Scope	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)
Backward Citations	0.004***	0.004***	0.004***
	(0.001)	(0.001)	(0.001)
Litigation	0.128***	0.128***	0.128***
	(0.014)	(0.014)	(0.014)
Firm × Filing-Year FE	Yes	Yes	Yes
R^2	0.432	0.432	0.432
Num. of Obs.	1,859,106	1,859,106	1,859,106

Table A5: Financial Consequences of Patent Transactions: Robustness Test

This table reports the result of a robustness test of financial consequences of patent transactions using a matched sample of seller and non-seller firms based on the closest propensity score. I match each seller firm with one non-seller firm (with replacement) in the same 3-digit SIC industry and transaction year that has the closest propensity score estimated using number of patents filed by a firm in the transaction year, total assets, R&D ratio, current year's ROA, leverage, current, cash, and capital expenditure. I combine a seller firm and the matched non-seller firm into a cohort, and then I stack all the cohorts of seller and matched non-seller firms to conduct DiD analysis. *Return on Assets* is defined as firm i's earnings before interest (EBIT) in year t divided by its book assets. *Operating Profitability* is defined as firm i's operating income before depreciation in year t divided by its book assets. *Assignor* is a dummy variable equal to 1 if firm i is the seller firm in a patent transaction. It is equal to 0 otherwise. *Post* is a dummy variable equal to 1 if the observation is within a three-year period after a patent transaction. It is equal to 0 otherwise. Firm-level control variables include *Total Assets*, which is calculated as logarithm of firm i's book assets in year t; *R&D*, calculated as the ratio of firm i's R&D expense to its book assets in year t; *Leverage*, calculated as the ratio of firm i's total debt to its book assets in year t; *Current*, calculated as the firm i's current assets divided by its current liabilities in year t; *Cash*, calculated as the firm i's cash holdings divided by its book assets in year t; and *CAPEX*, measured as the ratio of firm i's capital expenditure to its book assets in year t. Cohort-by-year fixed effects are included in both regressions. Standard errors are robust and clustered by firms. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	Return on Assets	Operating Profitability
	(1)	(2)
Assignor × Post	0.067**	0.062**
	(0.031)	(0.030)
Assignor	0.062	0.074
	(0.055)	(0.054)
Firm-level Controls	Yes	Yes
Cohort × Year FE	Yes	Yes
Adj. R^2	0.962	0.964
Num. of Obs.	9,020	9,000

Table A6: Financial Consequences of Patent Transactions: Decomposition of ROA and Change in TFP

Sales is defined as the natural logarithm of firm i's total sales in year t. *SG&A* is defined as firm i's selling, general and administrative expense in year t divided by its book assets. *COGS* is constructed as firm i's cost of goods sold in year t scaled by its book assets. *TFP* is firm i's revenue-based total factor productivity in year t, constructed following the methodology of Olley and Pakes (1996). Firm-level control variables include *Total Assets*, calculated as the natural logarithm of firm i's book assets in year t; *R&D*, calculated as the ratio of firm i's R&D expense to its book assets in year t; *Leverage*, calculated as the ratio of firm i's total debt to its book assets in year t; *Current*, calculated as the firm i's current assets divided by its current liabilities in year t; *Cash*, calculated as the firm i's cash holdings divided by its book assets in year t; and *CAPEX*, measured as the ratio of firm i's capital expenditure to its book assets in year t. Industry-by-year fixed effects are included in all regressions. Robust standard errors are clustered by firms. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	Sales	SG&A	COGS	TFP
	(1)	(2)	(3)	(4)
Assignor × Post	0.041***	-0.030***	0.013**	0.120***
	(0.010)	(0.007)	(0.006)	(0.013)
Assignor	0.002	0.111***	0.020**	-0.237***
	(0.014)	(0.009)	(0.010)	(0.019)
Firm-level Controls	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.910	0.577	0.284	0.318
Num. of Obs.	128,057	119,725	135,154	115,218

Table A7: American Inventors Protection Act of 1999 and Patent Transaction Incidence

The dependent variable *I(Selling Patent)* is an indicator variable equal to 1 if firm i sells a patent in year t. It is equal to 0 otherwise. *I(Year >2000)* is a dummy variable equal to 1 if the unit of observation is after year 2000 and equal to 0 otherwise. Firm-level control variables include *Total Assets*, calculated as logarithm of firm i's book assets; *R&D*, calculated as the ratio of firm i's R&D expense to its book assets; *ROA*, measured as the ratio of firm i's EBIT (Earnings Before Interest) to its book assets; *Leverage*, calculated as the ratio of firm i's total debt to its book assets; *Current*, calculated as the firm i's current assets divided by its current liabilities; *Cash*, calculated as the firm i's cash holdings divided by its book assets; and *CAPEX*, measured as the ratio of firm i's capital expenditure to its book assets. Year trend is included in all regressions. 3-digit SIC industry and firm fixed effects are included in different regressions separately. Standard errors are robust and clustered by firms. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	I(Selling Patent)			
	(1)	(2)	(3)	(4)
I(Year > 2000)	0.010***	0.006**	0.008***	0.007**
	(0.002)	(0.002)	(0.003)	(0.003)
Year Trend	Yes	Yes	Yes	Yes
Firm Controls	No	Yes	No	Yes
Industry FE	Yes	Yes	No	No
Firm FE	No	No	Yes	Yes
Adj. R^2	0.028	0.093	0.248	0.244
Num. of Obs.	197,010	186,309	197,010	183,718

Table A8: Diff-in-Diff Analysis of the Impact of American Inventors Protection Act: Falsification Test

In this falsification test, to ensure the internal validity of my DiD estimator associated with the American Inventors Protection Act of 1999 in Table 10, I falsely assume that the Act related to patent application disclosure enacted three years before it actually did (i.e., year 2000). I thus estimate a three-year window around year 1997 on the sample of all assignor and non-assignor firms. *Return on Assets* is defined as firm i's earnings before interest (EBIT) in year t divided by its book assets. *Operating Profitability* is defined as firm i's operating income before depreciation in year t divided by its book assets. *Assignor* is a dummy variable equal to 1 if a firm is a seller firm in a patent transaction. It is equal to 0 otherwise. *Post* is a dummy variable equal to 1 if the unit of observation is within a three-year period after year 1997. It is equal to 0 otherwise. Firm-level control variables include *Total Assets*, calculated as the natural logarithm of firm i's book assets in year t; *R&D*, calculated as the ratio of firm i's R&D expense to its book assets in year t; *Leverage*, calculated as the ratio of firm i's total debt to its book assets in year t; *Current*, calculated as the firm i's current assets divided by its current liabilities in year t; *Cash*, calculated as the firm i's cash holdings divided by its book assets in year t; and *CAPEX*, measured as the ratio of firm i's capital expenditure to its book assets in year t. Industry-by-year fixed effects are included in both regressions. Robust standard errors are clustered by firms. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	Return on Assets	Operating Profitability
	(1)	(2)
Assignor × Post	0.093	0.090
	(0.137)	(0.137)
Assignor	0.013	0.017
	(0.029)	(0.029)
Firm-level Controls	Yes	Yes
Industry × Year FE	Yes	Yes
Adj. R^2	0.422	0.421
Num. of Obs.	20,143	20,123

Table A9: Inventor Flows of Assignor Firms Following Patent Transactions

Inventor_Flow$_{t+1}$ is the number of flow of inventors of a firm in year t+1. If this measure is positive (negative), it indicates that the firm experiences an inflow (outflow) of inventors in year t+1. *Inventor_Flow$_{t+2}$* and *Inventor_Flow$_{t+3}$* are defined similarly. *I(Selling Patent)* is an indicator variable equal to 1 if firm i sells some of its patents in year t. It is equal to 0 otherwise. Firm-level control variables include *Total Assets*, calculated as the natural logarithm of firm i's book assets in year t; *R&D*, calculated as the ratio of firm i's R&D expense to its book assets in year t; *ROA*, measured as the ratio of a firm's EBIT (Earnings Before Interest) to its book assets; *Leverage*, calculated as the firm i's total debt scaled by its book assets in year t; *Current*, calculated as the firm i's current assets divided by its current liabilities in year t; *Cash*, calculated as the firm i's cash holdings scaled by its book assets in year t; and *CAPEX*, measured as the ratio of firm i's capital expenditure to its book assets in year t. Firm and year fixed effects are included. Standard errors are robust and clustered by firms. *, **, and *** denote the 10%, 5%, and 1% significance level, respectively.

	Inventor_Flow$_{t+1}$	Inventor_Flow$_{t+2}$	Inventor_Flow$_{t+3}$
	(1)	(2)	(3)
I(Selling Patent)	5.787**	6.548**	7.333***
	(2.660)	(3.183)	(3.454)
Firm-level Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Adj. R^2	0.562	0.558	0.561
Num. of Obs.	49,041	46,678	44,118