

A Dynamic Model of the Impact of Pre-Discovery Licensing on Innovation and Product Market Efficiency: Evidence from the Semiconductor Industry*

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Abstract

This study evaluates the impact of pre-discovery licensing on innovation and product market efficiency. Pre-discovery licensing is a form of R&D cooperation between firms, which accounts for more than 95% of all research collaborations. Pre-discovery licensing is pursued independently between firms, i.e., without governmental support. In contrast, in a research joint venture firms cooperate in R&D, as they usually seek protection and support from government enacted laws and programs which gives rise to selection problems. Despite existing work on research joint ventures, there has been little work on pre-discovery licensing. The estimation results of our dynamic count data model show that pre-discovery licensing reduces innovative activity. We continue to estimate a semi-structural model, which provides evidence that pre-discovery licensing agreements increase costs in the product market. Our results show that pre-discovery licensing increased the price of a semiconductor chip by \$0.225. Hence, consumers paid a total amount of \$1.6 billion more per year due to the fact that pre-discovery licensing agreements increase costs. Our findings stand in contrast to the empirical findings on research joint ventures, emphasizing the notion that selection is a critical argument which causes different results.

JEL: L11, L13, L52, O31, O32, O38.

Keywords: Collusion, Count Data, Innovation, Pre-Discovery Licensing, Research Joint Ventures, R&D Cooperation, Semiconductor, Strategic Alliances.

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1 Introduction

The invention of new technologies is one of the key drivers for firm productivity and economic growth. Firms frequently engage in research and development collaborations to coordinate and pool resources, which promotes technological progress and keeps up with increased international competition. Research and development collaborations have become commonplace especially in high-tech industries, such as the semiconductor, pharmaceutical and electronic product industries.

Pre-divestiture licensing is the most common type of research collaborations performed between firms. They are non-equity collaborations, in which firms acquire the right to use future inventions of their contracting partners, and are formed before an invention has been made. More than 95% of research collaborations in the semiconductor industry –one of the key industries influencing economic growth– are pre-divestiture licensing collaborations. Another type of R&D cooperation is the research joint venture (RJV).¹ Even though only 1% of all research collaborations are RJVs, the impact of RJVs on innovation has been extensively investigated in prior literature.² The vast majority of empirical studies found that RJVs have a positive impact on innovation, see, e.g., Branstetter and Sakakibara (2002 and 2003), Irwin and Klenow (1994), and Roeller, Siebert and Tombak (2007), among many others. Very surprisingly, even though most R&D collaborations represent pre-divestiture licensing agreements, little is known about their impact on technology and product markets. To date, only a few empirical studies concentrate on licensing, see e.g. Galasso (2012), Arora and Fosfuri (2003), Arora and Ceccagnoli (2006), Gans et al. (2002), Anand and Khanna (2000) and Siebert and von Graevenitz (2010). These studies concentrate on post-divestiture licensing agreements. To the best of our knowledge, there is no empirical study that investigates the impact of pre-divestiture licensing agreements on innovation and efficiency in the product market.³

¹RJVs are usually jointly owned (equity) research facilities.

²Prior studies exclusively focused on RJVs, as information on RJV participation became publicly available. The data availability eventually motivated further empirical work.

³Post-divestiture licensing agreements refer to agreements in which patents are licensed after the discovery of an invention has been made. Hence, they are fundamentally different from pre-divestiture licensing agreements. It should also be noted that most theoretical studies concentrate on post-divestiture licensing agreements. Prominent studies are the following: Katz and Shapiro (1987) examine how licensing between duopolists affects the speed of innovation. Gallini (1984) highlights the fact that licensing can be used by an incumbent to deter a potential entrant from doing its own R&D. Gallini and Winter (1985) demonstrate that incumbents have an incentive to license innovations to competitors so as to weaken rivals' future R&D incentives. Kamien, Muller and Zang (1992) focus on the interplay between technological spillovers and product market differentiation determines firms' incentives to form research joint ventures, and licensing. They also investigate the impact of those cooperations on R&D investments, efficiencies and prices in the product market. For private and social incentives to engage in

Many policy authorities recognize the beneficial impacts of RJVs on innovation. At the same time, they generalize their benefits to R&D collaborations overall. The question arises, however, if their beneficial outcomes can be generalized from RJVs to pre-divestiture licensing agreements (PDLs). This is a reasonable question for the following reasons.

First, while more than 95% of the research collaborations in the semiconductor industry represent PDLs, less than 1% are RJVs.⁴ Consequently, existing empirical evidence is based on a small sample of RJVs, which represents only a small subset of research collaborations. Hence, they are likely to be subject to a rare events problem and more general inferences towards research collaborations raise serious doubts and concerns, as they are based on a small subset of cooperations, i.e., RJVs.

Second, many countries initiated R&D programs and enacted laws which serve the purpose to spur economic growth and to increase firms' incentives to form RJVs. In fact, firms participated in those programs and formed RJVs to receive governmental protection for potential antitrust and litigation incidences (e.g., NCRA in the U.S.), subsidies (e.g., the EUREKA program from the EU and MITI in Japan), or tax redemptions. Regulations require RJVs to be registered with the government and to reveal the research objectives, which gives rise to firms being selective in registering RJVs. Firms are aware that registration increases the likelihood of being subject to scrutiny, and register only those RJV projects that tend to be welfare enhancing. R&D projects that are unlikely to improve welfare may not to be registered.⁵ Firms frequently engage in PDL agreements and pursue their collaborations independently and without the governmental support provided by the enacted programs.⁶ Firms avoid the revelation of information about their participation and their research objectives.

Both arguments give rise to the concern that empirical findings on RJVs are based on a small subset of firms that self-selected themselves into R&D projects which were less likely to cause harm to consumer surplus. Serious doubts and concerns are justified that general inferences towards research collaborations are problematic due to selection bias and rare events problems. Hence, the results for RJVs are constrained to a self-selected sample of firms, and cannot be

post-diversity licensing agreements, see also Nordhaus (1969) and Tandon (1982).

⁴It may be so low because of the high overhead costs to form and manage an RJV, as those form own entities. In contrast, PDL collaborations are not necessarily performed in the same entity. The high overhead and monitoring costs were also considered to be one reason responsible for the fairly large failure rate of RJVs, which is (45%).

⁵For an overview of the research joint ventures characteristics registered with the U.S. Department of Justice between 1985 and 1995, see Vonortas (1997).

⁶Grindley and Teece (1997) highlight the fact that licensing is also used as an instrument to guarantee freedom to operate in the technological market.

easily generalized to R&D collaborations or PDLs. The objective of our study is to investigate the impact of the more commonly applied type of R&D collaboration, i.e., PDL, on innovation and product market efficiency.

In general, firms may experience a variety of benefits when engaging in research collaborations which have positive implications on consumer surplus. For example, collaborating firms benefit from R&D investments being complementary assets. Firms avail themselves of an opportunity to exchange and absorb knowledge from their competitors, see Cassiman and Veugelers (2002), Bloom, Schankerman and van Reenen (2013) and Kamien, Muller, and Zang (1992). Moreover, R&D cooperations can be used as an instrument to overcome free-rider problems in R&D (see, e.g., Goeree and Hinloopen, 2008), to avoid wasteful duplications in R&D spending, to internalize negative profit externalities, to save on fixed costs and to reduce their risks in R&D (see Grossman and Shapiro, 1986, d'Aspremont and Jacquemin, 1988, and Ordoover and Baumol, 1988). Policy makers are aware of the arguments and encourage such collaborations.

Research collaborations also have the potential to cause harm to consumer surplus. Several studies on RJVs mentioned that RJVs may facilitate collusive behavior in the product market, see e.g., Cabral (2000), Martin (1995), Goeree and Helland (2010), Duso, Roeller and Seldeslachts (2013) and Suetens (2008). Those studies explicitly considered the possibility of firms colluding in the product market, i.e., fixing product prices. It should be noted, however, that price fixing is only one among many alternatives for firms to coordinate activities that harms consumer welfare. Research collaborations could be used as an instrument to coordinate firms activities and to delay new inventions, which lowers firms' R&D activities. Since the replacement of a proceeding technology might cannibalize firms' ongoing sales generated by an existing technology, firms might have an incentive to cooperatively delay the introduction of a new technology and to keep ongoing profit-streams.⁷ In this case, the efficiency in the product market declines due to the fact that collusive behavior is performed in the technological market, rather than the product market via price fixing. Ignoring any potential collusive behavior in the technology market (such as delaying new technologies) would leave anticompetitive implications on the product market undetected. Another argument that conceals a drawback on innovation is free-riding on a partner's R&D efforts. To summarize, the question arises, if PDLs should raise concerns from a policy point of view.

⁷The argument builds on literature related to the optimal timing of adopting new technologies, see e.g., Reinganum (1989) and Tirole (2003).

In order to analyze this question, we use a novel and comprehensive database on PDLs performed in the semiconductor industry between 1989 and 1997. We evaluate their firm-level impact on innovation in the semiconductor industry, as well as their firm-level impact on product market efficiency.⁸ Evaluating the impact of PDLs on innovation at the industry level is challenging as R&D investments for specific industries are usually unobserved.⁹ Our underlying economic model characterizes a relationship between PDL, innovative output and R&D investments, which allows us to evaluate an industry-specific impact on R&D investments. The model builds on a production function approach in which R&D investments enter as an input and patent counts enter as an output (see e.g., Crepon and Duguet, 1997a,b, Hall et al., 1986, Hausman et al., 1984, and Pakes and Griliches, 1984).

Our model accounts for the fact that firms' innovation activity in the semiconductor industry is described by a cumulative, state or path-dependent R&D process. Firms' past innovation activity determines their current knowledge and expertise in the technological market, which determines future profits, and future activities in R&D spending and PDL. We establish a dynamic model that incorporates a lagged dependent variable and treats it as a predetermined regressor.¹⁰

Our empirical model also controls for unobserved heterogeneity which is crucial to distinguish true from spurious state dependence.¹¹ Semiconductor firms are characterized by different abilities and strengths, which are difficult to measure or unobserved, such as managerial or engineering talent. Since more productive firms generate higher profits and invest more in R&D, the unobserved ability is potentially correlated with the regressors, such as R&D investments and PDL. We estimate a dynamic count data model, which allows the regressors to be correlated with unobserved heterogeneity. More specifically, we estimate a linear feedback model by Blundell, Griffith, and Windmeijer (2002).¹²

Our estimation results show that PDLs lower innovative activity in the semiconductor indus-

⁸Anand and Khanna (2000) remark that the level of licensing in the semiconductor industry is high, relative to other industries. This supports the fact that the semiconductor industry is a natural object to focus on.

⁹One alternative to generate industry-level R&D investments would be to break the firm-level R&D investments down in equal contributions according to the number of industries a firm operates in. This procedure, however, incorporates a potential (dis)aggregation bias, as it ignores that firms spend unequal proportions of their R&D budget in different industries.

¹⁰Our empirical model considers a feedback effect from the current dependent variable (patents) to future explanatory variables (R&D investments and PDL), i.e., future explanatory variables are correlated with current and past errors.

¹¹Spurious correlation can cause inconsistent estimates, see Heckman (1981).

¹²See also Bloom, Schankerman and van Reenen (2013) and Blundell, Griffith and Van Reenen (1999) for similar applications.

try by 5% or by about 5,000 patents throughout the 1989 to 1997 period. We find that firms eventually reallocate their R&D savings from the semiconductor market to other markets, e.g., electronic products. The R&D reductions from the semiconductor industry, however, are not fully passed on to other areas, thus the total innovative activity declines by only 2.5%. Our study provides evidence that PDLs can be used as an instrument to either delay the timing of new inventions or to free-ride on their partners' R&D investments, which avoids cannibalization of their sales generated by their current technology. This result is surprising, as previous studies on RJVs found that R&D cooperations increase technological activities. Hence, our results suggest that the rare events and self-selection problems (RJV participants select themselves into welfare improving projects) are critical aspects of the innovation process as they cause different results between RJVs and PDLs.

Finally, we apply a semi-structural model and derive testable restrictions on the firm's reduced form revenue equation which must be satisfied if PDLs increase or alternatively decrease costs. Our results provide evidence that PDLs lower innovative activity and increase costs and prices in the product market. Our results show that customers paid \$0.225 more for a chip due to the fact that PDLs reduced innovative activity and increased costs. This adds up to an annual total amount of \$1.6 billion that was paid more by consumers due to PDLs increasing costs. This result stands in contrast to the empirical findings on research joint ventures, emphasizing the notion that selection mechanisms is a critical argument which generates different results. This result is especially interesting as previous studies on RJVs concentrated on welfare-decreasing actions of RJV participants, originating from price-fixing behavior in the product market. Our study draws attention to another anticompetitive action, i.e., R&D cooperations and PDLs (representing the vast majority of research collaborations) reduce innovative activity, which increases costs and prices in the product market.

The rest of the paper is organized as follows. Section 2 provides information on the industry and the dataset. Section 3 introduces the empirical model. In Section 4, we discuss econometric issues and explain the estimation of the model. Section 5 presents the results of the dynamic count data model. Additionally, we derive our semi-structural model and discuss the estimation results. We conclude in Section 6.

2 Industry and Data Descriptives

The semiconductor industry is one of the key industries that promotes economic growth. Jorgenson (2001) has shown that innovations in the semiconductor industry have a crucial impact on other downstream industries, such as electronics and telecommunications. Semiconductors are mainly used as inputs for the computer industry, consumer electronics, and communications equipment. The semiconductor market consists of memory chips, micro components, and other components such as logic devices. R&D collaborations are an important instrument in the semiconductor industry as it allows firms to keep up with the high pace of innovation (Hall et al., 2001). In fact, firms in this industry are engaged in a large number of PDL agreements.

We gathered data from a variety of sources. Thompson Financial provided us with information on PDL agreements between firms in the semiconductor industry. The data are collected from different sources, e.g. professional data providers, consulting projects, business reports, Lexis/Nexis, Electronic News, Electronic Business etc.¹³ We concentrate in the empirical analysis on horizontal PDL agreements, and exclude licenses for production and marketing, as well as vertical alliances. During the 1989 – 1997 period, 617 PDL agreements that have been signed, an average of 70 PDLs per year. Table 1 shows the Top 10 firms involved in PDLs over the sample period, with International Business Machines (IBM) engaged in the most PDLs. Table 2 displays annual statistics on firms' average PDLs. The number of PDLs increased from 29 in 1989, to 112 in 1994, and then declined to 42 in 1997.

Gartner, Inc. provided data on firms' production volume in the semiconductor industry. The data covers more than 95% of all international producing semiconductor firms. Our database contains the firm-level semiconductor-specific revenues from 1989 until 1997. Table 2 shows that the average market shares of firms almost continuously declined from 0.77% in 1989 to 0.56% in 1997. In the 1990s, competition in the semiconductor industry increased dramatically, brought on by the larger number of firms, which rose from 132 in 1989 to 187 in 1998. The semiconductor sales in the industry increased from 57 billion US-\$ in 1989 to 150 billion US-\$ in 1997.

Moreover, we identified the patents that each firm holds overall and in the semiconductor industry on all inventions that have been applied and subsequently granted in the U.S. The

¹³Consultants in the industry confirmed that the dataset provides a comprehensive record and a close to complete sample of PDL activity in the semiconductor industry. Given the fact that the data provider itself is engaged in numerous consulting projects in the industry it increases the reliability of having an almost complete set of PDLs.

patent data themselves were procured from the U.S. Patent and Trademark Office. We use U.S. patents because the U.S. is the world’s largest technology marketplace and it has become routine also for non-U.S. based firms to patent in the U.S. (see Albert et al., 1991). The patent data are provided by the NBER patent database established by Hall et al. (2001). The database comprises detailed information on almost 3 million U.S. utility patents granted between January 1963 and December 1999, and includes citations made to these patents between 1975 and 1999 (over 16 million).¹⁴ Each patent contains highly detailed information on the innovation itself, the application date (the date when the inventor applied for the patent), the inventors (e.g. their geographical location), the assignee, the patent or technology classes which it belongs to etc.¹⁵ Following previous literature, we use the patent counts and patent citations as indicators for innovative output and quality, respectively. We excluded individually owned patents.¹⁶

Table 2 shows the average number of patents held by a firm, and the average number of semiconductor patents held by a firm from 1989 to 1997. The number of total patents per firm doubled from 78,619 in 1989 to 143,109 in 1997. The number of semiconductor patents per firm tripled during this period from 4,063 to 13,507. The number of patents in the semiconductor industry represents a share of about 5% to 10% of the patents overall. Finally, we obtained firm-specific data such as the overall firms-specific R&D investments from the Moody’s database, which has information on 17,785 firms based on financial reports, and the business press.

The identity of semiconductor firms is then cross-linked with affiliations and acquisitions, as well as the other databases. Our dataset involves 263 unique firms indexed by $i = 1, \dots, 263$; a time period of $T = 8$ years referenced by the index t ; the initial year in our dataset is 1989. Descriptive statistics about the patent series and the R&D investments are shown in Table 3.¹⁷ For firm i at time t , the variables P_{it} , P_{it}^S , PDL_{it}^S , RD_{it} , and rd_{it} refer to the overall patents, semiconductor patents, PDLs in the semiconductor industry, R&D investments and the

¹⁴Hall et al. (2001) mention the complications in matching the patents data to firm data. Firms patent under a variety of names (their own and those of their subsidiaries). A large name-matching effort was undertaken that matches the names of patenting organizations to the names of manufacturing firms and 30,000 of their subsidiaries (obtained from the Who owns Who directory).

¹⁵The U.S. Patent and Trademark Office has developed over the years a highly elaborate classification system for the technologies to categorize the patented inventions, consisting of about 400 main (3-digit) patent classes.

¹⁶Note that patent counts are an appropriate measure for innovative output whereas citations are correlated with the value of innovations (Trajtenberg, 1990). For further studies that used citations as indicators of spillovers (see Jaffe, Trajtenberg and Henderson, 1993), or as measure for the broadness of innovative activity, i.e. “originality” and “generality” (see Trajtenberg, Jaffe and Henderson, 1997).

¹⁷Even though R&D investments are never used as a measurement in our analysis, they are indeed the input to the innovation process and, as we show further below, they play an important role in developing our econometric specification. Note that we do not have R&D investments at the semiconductor level.

logarithm of those investments, respectively. Throughout the paper, we use a superscript S to refer to the firm-level semiconductor data and, when there are no superscripts, we refer to the aggregate firm-level data. Table 3 illustrates the following facts: our dataset is characterized by a large proportion of zeros, the median number of patents is 0, the counts are small and positive, and we have pre-sample information on patents, i.e., a longer time series.

As shown in previous literature, state dependence is an important determinant of the innovation process and R&D cooperations. There are several reasons why current innovative activity is dependent on the past innovative activity. One explanation for path-dependency is that engagement in research programs lasts for more than one period. Another explanation is that technologies became increasingly complex, and multiple complementary patents are required to invent a new technology, see e.g., Clark and Konrad (2008) and Siebert and von Graevenitz (2010). Moreover, previous patents will determine firms' knowledge and expertise in the technology markets, which itself impacts current profits, their re-investment in R&D, and their technological output or patents. Another source of path dependency is given by the transaction cost argument. If a firm was innovative in the past period, it is more likely that it will be innovative in the current period, as transaction costs for collaborating, innovating and patenting are lower. Hence, we will have to account for the fact that innovative activity and patents are interrelated over time, or path dependent.

Next, we provide insights regarding the data characteristics in order to establish the appropriate model. We focus on two aspects, the persistence of R&D investments over time, and the relationship between PDL and R&D investments. Following Hall et al. (1986), we specify an autoregressive model of first and second order, respectively:

$$rd_{it} = \alpha_1 rd_{it-1} + \alpha_2 r_t^S + \alpha_3 PDL_{it-1}^S + \alpha_4 Firms_t^S + \eta_i + \varepsilon_{it} \quad (1)$$

and

$$rd_{it} = \beta_1 rd_{it-1} + \beta_2 rd_{it-2} + \beta_3 r_t^S + \beta_4 PDL_{it-1}^S + \beta_5 Firms_t^S + \tilde{\eta}_i + \tilde{\varepsilon}_{it} \quad (2)$$

where the dependent variable (rd_{it}) represents firm i 's R&D investments in period t . On the right hand side enter the lagged dependent variables (rd_{it-1} and rd_{it-2}), the semiconductor industry revenues (r_t^S), a dummy variable that refers to the fact that a firm participated in

a pre-divestiture licensing agreement (PDL_{it-1}^S), the number of firms in the semiconductor industry ($Firms_t^S$), and a firm fixed effect (η_i). We lag the PDL by one period to ensure a reasonable timing for licensing agreements having an impact on firm’s R&D investments.¹⁸

Before turning to the results we discuss several econometric issues for the estimation procedure. First, the lagged dependent variable is predetermined, and is correlated with past errors. Moreover, the lagged PDL variable is also a predetermined variable as it determines future innovation and revenues, and is also correlated with past errors. Both variables are potentially correlated with the fixed effect (η_i), which gives rise to a dynamic panel bias (Nickell, 1981). OLS estimation leads to potentially inconsistent estimates if the time dimension is small compared to the number of firms, as in our dataset. We account for this problem using the GMM estimator suggested by Arellano and Bond (1991), which builds on Holtz-Eakin et al (1988). Internal and external instruments are used for the lagged dependent variable and the PDL variable. Our internal instruments consist of further lags of the the firm-level revenues and the PDL. Since lagged levels are often poor instruments, we use additional external instruments. We follow earlier literature on RJVs and use the same established instruments as used in Roeller, Siebert and Tombak (2007), Gugler and Siebert (2007) and Duso, Roeller and Seldeslachts (2013). That is, we use the lagged stock of semiconductor patents, a measure of how efficiently firms innovate, which is an appropriate instrument for explaining PDL participation. We also used forward citations on firms’ patents in order to measure quality and a firm’s innovation strength. Moreover, we account for the fact that larger firms gain more from innovation as any achieved cost reductions can be passed on to a larger production scale. Finally, we follow Siebert and von Graevenitz (2013), which refers to the literature on transaction costs, and the fact that licensing agreements require legal and organizational expertise. We refer to their finding that experience in signing licensing agreements lowers those transaction costs, and also add lagged PDLs to the set of instruments.

We applied several tests to the GMM estimator. First, we test for the joint exogeneity of the moment conditions. Since the number of instruments is much larger than the potentially endogenous variables, we apply the Sargan statistic for over-identifying restrictions. The Sargan test has a null hypothesis that the instruments as a group are exogenous. Our test indicates a high p-value of 0.22, which states that we cannot reject the joint hypothesis that the over-

¹⁸Since R&D investments are frequently determined at the beginning of a period or year, we use the PDL from period t-1. A similar equation is estimated in which the R&D investments are replaced by patents.

identifying restrictions are valid. Hence, our instruments are not correlated with the residuals. Finally, the GMM estimation hinges on the assumption that the error terms are not serially correlated. We also applied the test for autocorrelation by Arellano and Bond, which has a null hypothesis of no autocorrelation. A p-value of 0.41 rejects autocorrelation in the disturbance terms.

The results for equation (1) are shown in Table 4, column 2. The first lag on R&D investments is close to 1, indicating that the time series is highly persistent.¹⁹ The results confirm our conjecture that firms' innovation activity is affected by choice dynamics, which is driven by state or path dependency. The current innovative activity depends on past innovative activity. Those results will be useful when we develop our econometric model to study the impact of PDLs on patents. The industry revenues positively impact R&D investments, indicating that larger markets induce more innovation. Most interestingly, our dummy variable (PDL) has a significantly negative impact on R&D spending at the overall firm-level. The main drawback with the regression is that we do not observe the R&D investments in semiconductors. Hence, we estimate the impact of PDLs on R&D investments at the overall firm-level and not on the semiconductor market level. The problem is that the R&D spending in semiconductors could have increased, and firms could have cut R&D investments in areas other than semiconductors. Since the results are vulnerable to an aggregation bias, the impact of PDL on innovations remains unclear at this point. Therefore, we establish a theoretical framework to further evaluate the impact of PDL on innovation in the semiconductor industry and product market efficiency.

Before we turn to our theoretical framework, however, we proceed analyzing different lags of R&D investments and estimate equation (2). The results (see Table 4, column 3) show the second lag of the dependent variable (r_{it-2}) is significantly smaller than the first lag. Hence, most of the R&D variation over time can be explained by the most recent lag and the addition of further lags does not add much explanatory power. This result is consistent with Hall et al. (1986).²⁰ The results provide evidence that the time series on R&D investments are properly explained by using a first-order autoregressive model.

¹⁹For convergence, the point estimate of the lagged dependent variable needs to be less than 1. Unit root tests indeed indicate that the market share data-generating process is stationary.

²⁰We ran regressions in which we replaced the R&D investments with patents at the firm-level and semiconductor-level. The results were similar to the reported one, indicating that the patent series is highly persistent over time.

3 The Empirical Model

Our underlying economic model is similar to Hall, Griliches and Hausman (1986), Hausman, Hall and Griliches (1984) and Blundell et al. (2002). Consistent with the prior literature (e.g., Pakes and Griliches, 1984, Cincera, 1997), we apply a production function approach in which patents are the innovative output to the knowledge production function and R&D investments are the corresponding input. Specifically, we assume the following Cobb-Douglas knowledge production function:

$$P_{it}^S = k\eta_i RD_{it}^{S,\beta} \quad (3)$$

where i refers to the firm and t to the period, P_{it}^S is the semiconductor patent count, RD_{it}^S refers to the semiconductor R&D investments, k is the productivity factor, and η_i captures firm-specific characteristics to patent. Rewriting this production function and adding an idiosyncratic error ε_{it} , results in:

$$P_{it}^S = \exp(\log(k\eta_i) + \beta \log RD_{it}^S) + \varepsilon_{it} \quad (4)$$

Note the following points regarding our knowledge production function. First, the relationship between R&D investments and patents is contemporaneous, as has been shown to be valid in the previous literature (see, e.g., Hall et al., 1986, and Hall and Ziedonis, 2001), and as has been frequently specified in this specific form, see also Kortum and Lerner (2000) and Bloom et al. (2013). Second, firm-specific characteristics enter in a multiplicative manner (Crepon and Duguet, 1997b, Montalvo, 1997, Blundell et al., 1995, 1999, 2002). Third, recall that we are interested in studying the industry-specific impact of PDLs on innovation in the semiconductor industry. Equation (4) does not directly allow us to investigate this relationship, as RD^S is unobserved, implying that the production function has to be re-specified.

The production function re-specification builds on the autoregressive equations we had considered earlier. Recall that our estimation results of equation (2) have shown that semiconductor PDLs have a significant impact on firm-level R&D investments. It is reasonable to expect that PDLs will have a significant impact on firm-level R&D investments in the semiconductor industry as well. Hence, we can establish a similar relationship in the context of semiconductor R&D

investments as well, i.e., $rd_{it}^S = \alpha_1 rd_{it-1}^S + \alpha_2 PDL_{it-1}^S$. Using this relationship, we can replace the contemporaneous R&D investments at the semiconductor level using PDLs in the previous period, and rewrite equation (4) as follows:

$$P_{it}^S = \exp((1 - \alpha_0) \log(\eta_i k) + \alpha_0 (\log P_{it-1}^S) + PDL_{it-1}^S \beta \alpha_1) + u_{it} \quad (5)$$

in which $E(u_{it} | PDL_{it-1}^S, P_{it-1}^S, \eta_i) = 0$. Depending on the serial correlation structure of ε_{it} , the process for u_{it} may display some autocorrelation. The re-specified multiplicative feedback model in equation (5) is still difficult to estimate. It runs into problems when transforming the zero values for the patents (see Table 3). To overcome such a problem in the specification, Cameron and Trivedi (2005, pg. 806) propose an alternative linear feedback model, which is based on the multiplicative feedback model. Rewriting equation (5), we get:

$$P_{it}^S = ((1 - \alpha_0) \log(\eta_i k) + PDL_{it-1}^S \beta \alpha_1) + \gamma P_{it-1}^S + u_{it}, \quad (6)$$

where γ is the new coefficient accounting for the linear feedback. The transformation is similar to that in Blundell et al. (2002). Note also that the patent equation has been similarly linearized in prior works (including Kortum and Lerner, 2000). Rewriting equation (6), and setting $\phi = \beta \alpha_1$ and $\lambda_i = (\eta_i k)^{1-\alpha_0}$, we get:

$$P_{it}^S = \exp(\log(\lambda_i) + PDL_{it-1}^S \phi) + \gamma P_{it-1}^S + u_{it}, \quad (7)$$

where λ_i represents the firm fixed effects. In the above equation, we estimate the parameters, ϕ and γ . Note also, since patents are non-negative, the mean value for P_{it}^S is bounded above zero. The first term in equation 7 is always non-negative and γ must be greater than zero.²¹ In the following section, we discuss the econometric issues related to the estimation of equation (7).

²¹Note that the arguments and the re-specifications above also hold for the total patents. In that case, the S superscripts are dropped on the patent variables consistent with our earlier notation.

4 Econometric Issues

We apply a count data model, since our patent data can take on non-negative integer values. Count data models might involve a non-linearity which is due the non-negative discrete choice nature of the data. For strictly positive variables, one often uses the natural log transformation in order to linearize the model. This does not work in our application, since we observe nonnegative values, or face corner solutions due to the fact that firms have zero patents. Hence, we cannot easily linearize our model, as we would not account for corner solutions and predict negative values. As we saw in Table 3, there is a large maximum on the number of patents, as well as a large number of zeros, in which case, the most popular functional form that ensures positivity is the exponential function.²²

Controlling for unobserved heterogeneity is especially important in dynamic panel data settings. Firms may intrinsically differ in their propensity to innovate and those differences may not be fully accounted for by the regressors. In order to make any inferences about true state dependence, we have to separate state dependence (using lagged dependent variables) from dynamic responses caused by unobserved heterogeneity and serial correlation. For example, if unobserved heterogeneities are correlated over time and are not properly controlled for, residuals will be serially correlated. Hence, previous innovation (lagged patents) may appear to be a determinant of future innovation solely because it is a proxy for such serially correlated unobserved heterogeneity. If there are true dynamic responses to exogenous variables that are omitted from the model, the lagged dependent variable may be spuriously significant simply because it is correlated with the omitted lagged exogenous variables. Not accounting for unobserved heterogeneity may lead to spurious instead of true state dependence and spurious correlation may lead to inconsistent estimates (see Heckman, 1981).

In linear models, an additive unobserved effect can be eliminated by using an appropriate transformation - such as differencing. Then, instrumental variables can usually be found for implementation in a generalized method of moments (GMM) framework. Accounting for unobserved heterogeneity in non-linear models such as the count data model is beset with difficult econometric problems in deriving usable moment conditions. Mullahy (1997) notes that, in such cases, the unobserved heterogeneity is not independent of the regressors, i.e., $E(PDL_{it}\lambda_i) \neq 0$.

²²For more information and surveys on count data models, see Cameron and Trivedi (1998), Winkelmann (2000), and Wooldridge (1997).

Consequently, even the estimators from a standard GMM will be inconsistent.

The usual panel data estimator for count models where the fixed effects are correlated with the regressors is the Poisson conditional maximum likelihood estimator (CMLE) developed by Hausman et al. (1984). The consistency of this estimator depends on having strict exogenous regressors. In our case, however, the regressors are not strictly exogenous. Consequently, the use of CMLE is ruled out. Chamberlain (1992) suggests transformations that eliminate the fixed effect from the moment conditions. He suggests a quasi-difference GMM estimator that allows the fixed effect to be correlated with the (predetermined) regressors.²³

One major drawback with the standard quasi-differenced GMM estimators is that it suffers from a weak instrument problem (instruments are weak predictors) and can be severely biased if the time series is persistent and if the time series is short.²⁴ Remember that the time series on the R&D and patent data was highly persistent, see Table 4. Moreover, the total duration in our dataset is only eight years, $T = 8$. However, notice from Table 2 that we have pre-sample data on patents. Our patent data series dates back to 1963, while the firm-level market data begins in 1989. By incorporating pre-sample information in the context of quasi-differencing, Blundell et al. (2002) develop a new estimator called the pre-sample mean estimator. Blundell, Griffith, and Windmeijer (2002) shows through Monte Carlo simulation that the pre-sample mean estimator performs significantly better than a standard quasi-difference GMM estimator if the time series is short and highly persistent. Therefore, for our analysis, we employ a linear feedback model using the pre-sample mean estimator by Blundell, Griffith, and Windmeijer (2002). In accordance with the traditional dynamic panel data literature, lagged endogenous variables and lagged regressors are suggested as instruments. In the context of the pre-sample mean estimator, Blundell et al. (2002) also includes the pre-sample mean of the dependent variable as an instrument to avoid the problem that lagged variables may be weak predictors of future changes of the endogenous variables in the differenced model. Given the fact that the total duration in our dataset is only eight years and the R&D patents are highly persistent over time the weak instrumental problem might be a concern in our study.

²³A regressor is predetermined when it is not correlated with current and future shocks, but it is correlated with past shocks: $E(x_{it}u_{it+j}) = 0, j \geq 0$ and $E(x_{it}u_{it-s}) \neq 0, s \geq 1$ if x_{it} is the regressor and u_{it} is the error term.

²⁴See Blundell, Griffith and Van Reenen (1999) and Bloom, Schankerman and Van Reenen (2013) using a pre-sample mean scaling method to control for fixed effects.

5 The Results

We estimate equation (7) using the pre-sample mean estimator by Blundell, Griffith, and Windmeijer (2002). We use a similar set of instruments as suggested in Blundell et al. (2002), i.e., we use lagged patents, lagged PDLs, lagged market shares, lagged number of firms in the technology market and the pre-sample mean of the dependent variable. The results are reported in Table 5. Columns 2, 3, and 4 correspond to the estimates which use instrumental variables lagged between $t-2$ and $t-j$, where $j = 2, 3, 4$, respectively. Note that all estimates are significant at the 1% significance level. After controlling for unobserved heterogeneity the lagged dependent variable, P_{it-1}^S , is always statistically significant, which provides evidence for path dependency in innovation. The estimate of 0.6 implies that the depreciation rate of patents is approximately 40%, which is higher than the estimates in previous studies which estimated the depreciation of patents to be around 15-20%. Our higher estimate of the depreciation factor reflects the high pace of innovation in the semiconductor industry. The parameter estimate PDL_{it-1}^S is significantly negative, and provides evidence that PDL in the semiconductor industry reduces the number of patents in the semiconductor industry. The estimate indicates that patents would have increased by 5% without PDL. However, even though the number of patents declines, it could be that the nature of inventions changed and became more drastic or of higher quality. The question arises, if the quality of the innovations increased due to PDL. We applied a robustness check and follow Lanjouw and Schankerman (2004) to account for patent quality. Hence, we weight the patent counts by patent citations and run the same regression as before. The results are not significantly different. The Sargan Test for overidentifying restrictions confirms the selection of the instruments. We also tested for serial correlation of the residuals. The test is an extension of the tests for serial correlation in Arellano and Bond (1991). Under the null hypothesis of no serial correlation, these test statistics are asymptotically $N(0,1)$ distributed. Consistent with a well-specified model, we can confirm first-order and reject second-order autocorrelation for the residuals, see also Windmeijer (2002, pg. 13).

Based on the results in Table 5, we evaluate the impact of PDLs on the patenting activity in the semiconductor industry by year and over the total time period 1990-1997, as shown in Table 6. The second column represents the number of patents observed in the semiconductor industry according to our dataset. The third column represents the predicted number of semiconductor patents. Comparing those two columns, the predicted number of patents is within two standard

deviation points of the observed number of patents and therefore confirms the good fit of our estimates. The fourth column shows the number of patents without PDL activities. Comparing the number of patents from columns 3 and 4, returns the change in patents if no PDLs were performed in the semiconductor industry. The number of patents without PDL is smaller than the predicted and the observed number of patents. Without PDLs, the number of patents drops by approximately 600 (1,000) patents every year compared to the predicted (observed) number of patents. Evaluating the change in the number of patents without PDL over the entire time period 1990-1997, shows that the number of patents drops by 4,826 (8,287) compared the predicted (observed) number of patents. To summarize, we provide evidence that PDLs slow down innovative activity in the semiconductor industry.

The question arises, however, if firms eventually reallocated their R&D investments from the semiconductor industry towards other areas. Next, we investigate if the reduction of innovation activity in the semiconductor industry has been passed on to the overall firm-level. If the reduction from the semiconductor industry has been fully reallocated to other areas, we expect a non-significant decline, or an increase of innovation activity at the overall firm level. To evaluate the impact of PDLs in the semiconductor industry on the overall firm-level innovative activity, we adopt equation (7) but consider patents at the overall firm-level.

$$P_{it} = \gamma P_{it-1} + \eta_i \exp(\delta PDL_{it-1}^S) + \varepsilon_{it}. \quad (8)$$

where P_{it} represents the total firm-level number of patents. We apply the same estimation technique and use the same set of instruments and the same length of time periods as above. The results are shown in Table 5 in the three rightmost columns. The coefficient on the lagged dependent variable P_{it-1} is again significantly positive of around 0.5, similar to the estimate on the semiconductor level. This result indicates that the same intertemporal underlying process holds at the firm-level as well as the semiconductor level.

The estimate for PDL_{it-1}^S is significantly negative. The estimate confirms a negative impact of PDLs performed in the semiconductor industry on the innovation activity at the overall firm-level. In comparing the impact, we recognize that the impact on innovation activity at the semiconductor level itself is twice as large as on the overall firm-level. Therefore, while half of the reduction in innovation activity on the semiconductor level has been passed on to the overall

firm-level, the other half has been reinvested in other areas. The Sargan Test as well as the test for serial correlation of the residuals return the same results as above.

Even though the innovative activity declines, it could still be the case that the efficiency in the product market could have increased, since PDLs may developed riskier technologies that generated even higher efficiency gains, with fewer patents. We therefore investigate the impact of PDLs in the semiconductor market on the efficiency in the semiconductor market. Overall, the efficiency gains and the impact on consumer surplus is what economists and policy makers are eventually interested in examining.

Based on comparative statics results, we investigate how PDLs and the associated changes in innovative activity relate to cost reductions and revenues changes in the semiconductor market. We apply a semi-structural model, along the lines of Panzar and Rosse (1987), and derive testable restrictions on the firm's reduced form revenue equation which must be satisfied if PDLs increased or decreased costs. An oligopoly model is considered which exhibits strategic interactions between firms, and which introduces interdependencies (i.e., endogenous variables beyond the control of the firm) into firms' structural revenue functions.²⁵ We assume n firms acting in a homogeneous product market. Every firm i chooses its output level y_i to maximize its profits

$$\pi_i = P(Y)y_i - C(y_i, PDL), \quad (9)$$

where P is the inverse demand curve, $Y = \sum y_i$ is the industry output and PDL stands for pre-divestiture licensing. The first-order condition for the i 'th producing firm is,

$$\frac{\partial \pi_i}{\partial y_i} = \lambda y_i P_Y + P - C_y = 0, \quad (10)$$

where the conjectural variation $\lambda = \frac{dY}{dy_i}$ measures the change in industry output as a result from firm i increasing output, y_i and $C_y = \frac{dC}{dy_i}$. Assuming symmetry, and setting $y_i = y^0$ and $Y^0 = ny^0$ into equation (10),

$$\lambda y^0 P_Y(ny^0) + P(ny^0) - C_y(y^0, PDL) = 0. \quad (11)$$

²⁵The following arguments closely follow Panzar and Rosse (1987).

Equation (11) defines a firm's output y^0 as an implicit function of the variables λ and PDL .

Totally differentiating equation (11) with respect to PDL yields

$$\frac{\partial y^0}{\partial PDL} = \frac{\frac{\partial^2 C}{\partial y \partial PDL}}{D^0}, \quad (12)$$

where $D^0 = [ny^0\lambda P_{YY} + (n + \lambda)P_Y - C_{yy}]$. Premultiplying both sides of equation (12) by PDL yields

$$PDL\left(\frac{\partial y^0}{\partial PDL}\right) = \frac{PDL\left(\frac{\partial^2 C}{\partial y \partial PDL}\right)}{D^0} = \frac{C_y}{D^0} < 0, \quad (13)$$

where the last equality follows from Seade (1980), who has shown that $D^0 < 0$ is required for the stability of the symmetric equilibrium. Dividing by y^0 establishes that the elasticity of the reduced form firm output equation, $y^0(PDL)$, is negative.

Next, we focus of firms' revenues, $R^0(PDL) = y^0 P(ny^0)$. Applying the chain rule to equation (13) and dividing by R^0 yields

$$\psi^0 = \frac{PDL\left(\frac{\partial R^0}{\partial PDL}\right)}{R^0} = (y^0 n P_Y + P) \frac{PDL\left(\frac{\partial y^0}{\partial PDL}\right)}{R^0} = \frac{R_Y C_y}{D^0 R^0} < 0 \quad (14)$$

where $R_Y = Y^0 P_Y + P$ is the industry marginal revenue curve, which is positive. Moreover, since $\frac{C_y}{D^0}$ is negative as shown above, and R^0 is positive, it follows that

$$\frac{PDL\left(\frac{\partial R^0}{\partial PDL}\right)}{R^0} = \frac{R_Y C_y}{D^0 R^0} < 0, \quad (15)$$

and the revenue elasticity with respect to PDL is negative.

Based on the semi-structural model, we can show that revenues will decrease (increase) if PDLs increase (decrease) costs. We therefore are interested in evaluating the impact of PDLs on revenues in the semiconductor market. Adopting a similar specification as above, as well as Mueller (1985) and Gugler and Siebert (2007), we estimate the following autoregressive equation accounting for unobserved heterogeneity,

$$R_{it}^S = \gamma_1 R_{it-1}^S + \gamma_2 PDL_{it-1}^S + \gamma_3 P_{it}^S + \gamma_4 M S_{it}^S + \gamma_5 R_t^S + \gamma_6 Firms_t^S + \eta_i + \eta_t + \varepsilon_{it}, \quad (16)$$

where R_{it}^S is the dependent variable representing the firm-level revenues in the semiconductor industry in period t . The lagged dependent variable, R_{it-1}^S , is included as an regressor to account for persistences of revenues over time. PDL_{it-1} is again a dummy variable that refers to the fact that a firms participated in a pre-divestiture licensing agreement, lagged by one period. The PDL variable measures deviations from the firms revenue trend. We also include firm-level annual patents P_{it}^S in the semiconductor industry in period t to account for innovation having an impact on production costs. Moreover, we use firm-level market shares, Ms_{it}^S , in the semiconductor industry, and industry revenues (R_t^S) as a demand shifter. The number of firms in the semiconductor industry ($Firms_t^S$) serves as a control for the competitiveness in the product market, and the time fixed effect (η_t) controls for a potential omitted variable bias.

Similar to above, we briefly discuss several econometric issues for the estimation procedure. Since the lagged dependent variable and the lagged PDL variable represent predetermined variables, they are correlated with past errors. Since both variables are potentially correlated with the fixed effect (η_i), OLS estimation leads to potentially inconsistent estimates if the time series is short, see Nickell (1981). We use the GMM estimator by Arellano and Bond (1991). Similar to the estimation procedure above, we include three types of instruments the lagged dependent variable and the PDL variable. Our internal instruments are further lags of the the firm-level revenues and the PDL. For our external instruments, again, we follow Roeller, Siebert and Tombak (2007), Gugler and Siebert (2007), Duso, Roeller and Seldeslachts (2013) and Siebert and von Graevenitz (2013) and use the lagged stock of semiconductor patents, forward citations on firms' patents, firm size and lagged PDLs. Finally, we include all strictly exogenous variables into the instrument matrix. A potential problem with instruments is that the number of instruments may be large relative to number of observations. A suggested rule of thumb is to keep number of instruments smaller than the number of groups. We therefore use no more than two lags for our instruments.²⁶ The results are shown in Table 7.

The parameter estimate for the lagged revenue provides evidence that revenues are strongly persistent over time. Around 69% of the current revenues are explained by the lagged revenues. For convergence, the point estimate of the lagged dependent variable needs to be less than 1. Unit root (Fisher) tests reject the null hypothesis that the panels contain unit roots (at the 1% significance level) and confirm that the revenue data-generating process is stationary.

²⁶It should be mentioned, that checked for different lags and counts for the internal instruments.

The parameter estimate for PDL is significantly negative. According to the semi-structural model, the negative estimate provides evidence that PDLs decreased revenues and must have increased costs. The estimation results show that one PDL agreement lowers revenues by approximately \$90 million, which corresponds to a 11% decline in a firm's revenues. Accounting for the fact that on average 68 PDLs are signed per year, it corresponds to a change in industry revenues of \$6.1 billion, which corresponds to a 5% decline in industry revenues. Next, we go one step further and calculate the loss in consumer surplus, due to the fact that PDLs increase costs and prices, and consumers eventually have to pay a higher price for semiconductor chips. Referring to our estimated 5% decline in industry revenues and accounting for an established price elasticity of demand of -2 (see, e.g., Siebert, 2010, Zulehner, 2003, and Flamm, 1993, for estimated price elasticities in this neighborhood), it follows that PDLs increased the price by 1.5%. Next, we form an average semiconductor price based on the main semiconductor components, such as DRAMs and SRAMs and Flash memories for different generations from 1974 until 1999.²⁷ Using this average price of 15 dollars per semiconductor chip, results in 7.14 billion shipments sold to customers per year. Using those numbers results in the fact that customers paid \$0.225 more for a chip due to PDLs, which adds up to a total amount of \$1.6 billion that was paid more by consumers per year as a result to PDLs increasing costs. To summarize, our results provide evidence that PDLs lower innovative activity, which lowers costs and increases prices in the product market. This result is especially interesting as previous studies found that RJVs are beneficial to consumer surplus. Hence, our results suggest that the rare events and self-selection problem (RJVs participants select themselves into welfare improving projects) are important aspects that drive different results between RJVs and PDLs. Given that PDLs represent the vast majority of research collaborations, this finding raises serious antitrust concerns.

Turning to the semiconductor patent estimates, it is interesting to note that have they a positive significant impact on firm-revenues. Since patents reflect process innovations in the semiconductor industry, the positive estimate represents the fact that cost savings translate into revenue increases. The estimate shows that firms' annual patents increase revenues by more than \$250 million per year. The positive estimate also confirms the reliability of our test of the relationship between innovation, costs and revenues, based on estimating the semi-structural model. The model correctly reflects the fact that cost reductions (increases) will translate into

²⁷The data were provided by Gartner, Inc.

increases (reductions) in revenues.

We also applied several tests to the GMM estimation procedure. First, we test for the joint exogeneity of the moment conditions. Since the number of instruments is much larger than the potentially endogenous variables, we apply the Sargan statistic for over-identifying restrictions. The Sargan test has a null hypothesis that the instruments as a group are exogenous. Our test indicates a high p-value of 0.42, which states that we cannot reject the joint hypothesis that the over-identifying restrictions are valid. Hence, our instruments are not correlated with the residuals. Finally, the GMM estimation hinges on the assumption that the error terms are not serially correlated. We also applied the Arellano-Bond test for autocorrelation which has a null hypothesis of no autocorrelation. A p-value of 0.26 rejects autocorrelation in the disturbance terms.

6 Conclusion

Using a novel dataset on PDLs in the semiconductor industry, we estimate the impact of PDLs on innovation and efficiency in the product market. Estimating a dynamic count data model, our results show that PDLs lower innovative activity in the semiconductor market. The estimates show that 5% or about 5,000 more inventions would have been patented in the semiconductor industry if firms did not engage in PDLs. We also investigate if firms eventually reallocate their R&D savings from the semiconductor market to other markets. We find that firms reallocate only half of their savings in R&D investments from the semiconductor market towards other areas. Finally, we test if PDLs generate more drastic innovations and achieve higher efficiency gains in the product market. We apply a semi-structural model and derive testable restrictions on the firm's reduced form revenue equation which must be satisfied if PDLs increased or decreased costs. Our results provide evidence that PDLs lower innovative activity, lower costs and increase prices in the product market. The estimation results show that customers paid \$0.225 more for a chip due to PDLs, which adds up to a total amount of \$1.6 billion that was paid more by consumers per year due to PDLs increasing costs. This result is especially interesting from a consumer welfare and antitrust point of view. Note that we do not pinpoint the reasons for a reduction in product market performances. Possible explanations, however, are that firms free ride on their partners' investments, or that firms intentionally delay new inventions to avoid cannibalizing their sales generated by current technologies.

In comparing those results on PDLs with RJVs, we get the following interesting result. While previous studies on RJVs found that RJVs increase innovative activity, our study shows that PDLs decrease innovation and also lower the efficiency in the product market. Therefore, rare events and selection problems in RJVs originated by self-reporting memberships in RJVs generate different results between RJVs and PDLs. While RJV participants select themselves into beneficial projects, PDLs lower innovation and product market performance. Given that PDLs represent the vast majority of research collaborations, this raises serious antitrust concerns. From a policy point of view, one concern with RJVs is that participating firms might use the RJV as an instrument to collude and fix product prices. Our study on PDLs shows that even when we abstract from any price-fixing attempts in the product market, PDLs still represent a serious concern for policy makers, as they are potentially harmful to consumer welfare; they lower innovative activity and increase costs and prices the product market. Gaining insights in developing policy recommendations will surely go a long way in the intellectual property contexts.

More work in this area would be desired and there are various extensions to this study feasible. First, it would be interesting to examine if the impact of PDLs on the technological and product market also applies to different industries, such as the pharmaceutical and electronic products industry. Second, it would be interesting to gain further insights if different types of licensing agreements, i.e., pre-divestiture licensing, post-divestiture licensing, cross-licensing, have different impacts on innovative activity and product market efficiency.

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6.1 Appendix

The Estimator by Blundell, Griffith, and Windmeijer (2002)

We introduce the pre-sample mean estimator by Blundell et al. (2002), which we apply to estimate our dynamic count data model, allowing for unobserved heterogeneity and predetermined variables.²⁸ A common problem with the GMM estimation of standard (quasi-) differenced models is that they suffer from a weak instrumental problem. They can be severely biased if samples are small and if the time series of variables, such as patents and $R\&D$, is highly persistent over time. In this case, the instruments are weak predictors of future changes of the dependent variable. Blundell et al. (2002) show through Monte Carlo simulation that the pre-sample mean estimator (inclusion of pre-sample information in the context of quasi-differencing) performs significantly better than a standard quasi-difference GMM estimator. In general, we consider an input-output relation, or a production function of the following form:

$$Q_{it} = g(RD_{it}, RD_{it-1}, \dots, \beta, \eta_i)$$

where RD_{it} is the input (R&D investments), and Q_{it} is the technological output for firm i , $i = 1, \dots, N$, at time $t = 1, \dots, T$. The vector of unknown technology parameters is denoted by β , and η_i captures unobserved heterogeneity or a firm-specific propensity to produce technological output.

Let P_{it} describe observed patents, a discrete count variable, which is a noisy indicator of a firm's technological output:

$$P_{it} = Q_{it} + \varepsilon_{it}$$

with $E(\varepsilon_{it} | RD_{it}, RD_{it-1}, \dots, \beta, \eta_i) = 0$.

Suppose that historic R&D investments are combined through a Cobb-Douglas technology to produce knowledge stock. In this case, $Q_{it} = g(RD_{it}, RD_{it-1}, \dots, \beta, \eta_i)$ becomes $Q_{it} = RD_{it}^{\beta_1}, RD_{it-1}^{\beta_2}, \dots, \eta_i$. This motivates the conditional mean specification in a multiplicative dis-

²⁸Part of the description is based on Blundell, Griffith, and Windmeijer (2002, pg. 120).

tributed lag model:²⁹

$$E(P_{it} | RD_{it}, RD_{it-1}, \dots, RD_{it-p}, \eta_i) = \exp(rd_{it}\beta_1 + rd_{it-1}\beta_2 + \dots + rd_{it-p}\beta_{p+1}) \eta_i$$

where $rd_{it} = \ln RD_{it}$. If the R&D or patent series is highly persistent (see Table 4), the alternative dynamic specification of the linear feedback model can be attractive, which defines the following regression function:

$$P_{it} = k \left(RD_{it}^\beta + (1 - \delta) RD_{it-1}^\beta + \dots \right) \eta_i + \varepsilon_{it} \quad (17)$$

in which k is a positive constant and where the R&D investments depreciate exponentially at rate δ . The distributed lag term in brackets represents the process by which patents are produced from R&D inputs. Ignoring any feedback from patents to R&D, the long run steady state for firm i may be written as:

$$P_{it} = \frac{k}{\delta} RD_i^\beta \eta_i$$

so that β may be interpreted as the long run elasticity. In order to introduce the dynamic component into the model, we apply a linear feedback effect model.³⁰ In the formulation of dynamics, we apply the dynamic completeness conditional on the unobserved heterogeneity. Hence, we assume that the dynamics follows a first-order Markov process.³¹

Inverting equation (17), this leaves us with the following dynamic count data model:

$$P_{it} = k RD_{it}^\beta \eta_i + (1 - \delta) P_{it-1} + u_{it} \quad (18)$$

in which $E(u_{it} | RD_{it}, P_{it-1}, \eta_i) = 0$. Depending on the serial correlation structure of ε_{it} , the

²⁹The multiplicative distributed lag model is the standard model used in the R&D patents literature on count data, where lags of the regressors enter the exponential mean function.

³⁰Introducing dynamics into the count models is not straightforward as the conditional mean is required to remain positive. Inclusion of functions of the lagged dependent variable in the exponential function can lead to explosive series or to problems with transforming zero values. The dynamic specification considered here is a linear feedback model, where the lagged dependent variable enters the conditional mean specification linearly. Another commonly used dynamic specification for count data is the multiplicative distributed lag model, where lags of the regressors enter the exponential mean function.

³¹This is a reasonable assumption as the reduced form regressions show that accounting for one lag is sufficient to capture dynamics in the R&D process.

process for u_{it} may display some autocorrelation. We can write the following regression model,

$$P_{it} = \gamma P_{it-1} + \exp\left(rd'_{it}\beta + \eta_i\right) + u_{it} \quad (19)$$

with $\gamma > 0$, as only positive association is possible. Since $\exp\left(rd'_{it}\beta + \eta_i\right)$ is non-negative, the means value for P_{it} is bounded below by γP_{it-1} . Since $E(rd_{it}\eta_i \neq 0)$ standard random effects estimators will be inconsistent. Equation (19) is equivalent to equation (18), where the autoregressive coefficient γ represents the depreciation parameter $(1 - \delta)$, and β is the long run elasticity.³²

Rearranging equation (19) as described in our model section, we get:

$$P_{it} = \gamma P_{it-1} + \eta_i \exp\left(\delta PDL_{it-1}^S\right) + \varepsilon_{it}. \quad (20)$$

For predetermined regressors, the sample moments for the pre-sample mean estimator for the linear feedback model are $\sum_{i=1}^N \sum_{t=2}^T z_{it} (P_{it} - \gamma P_{it-1} - \exp(\phi_0^* + PDL_{it-1}\phi + \omega \log \bar{P}_i)) = 0$ where z_{it} is the set of instruments and \bar{P}_i is the pre-sample mean of the endogenous variable. The constant ϕ_0^* is shifted by $\frac{\log(1-\gamma)}{\omega}$. The traditional dynamic panel data literature suggests the use of the lagged endogenous variables and the lagged regressors as instruments. In the context of the pre-sample mean estimator, Blundell et al. (2002) also include the pre-sample mean of our dependent variables as an instrument.

³²With *strictly exogenous regressors*, the conditional mean of P_{it} satisfies $E(P_{it} | \eta_i, RD_{it}) = E(P_{it} | \eta_i, RD_{it}, \dots, RD_{iT})$. For this case, several estimators have been proposed that allow for individual effects to be correlated with the regressors see e.g. Hausman, Hall, and Griliches (1984) who use the Poisson conditional maximum likelihood estimator, conditioning on $\sum_{t=1}^T P_{it}$, which is the sufficient statistic for η_i . The estimator, however, gives inconsistent estimates if the regressors are predetermined (past patents) and therefore not strictly exogenous.

Table 1: Top PDL Firms

Top 10 Firms in PDL	PDLs (from 1989-1997)
IBM	38
Motorola	36
Texas Instruments	30
Toshiba	30
Intel	26
NEC	23
Mitsubishi	22
Hitachi	19
Ntl. Semiconductor	19
NEC	19

Table 1 presents the number of the top 10 PDL firms in the semiconductor industry from 1989-1997. The dataset is provided by Thompson Financial, Inc.

Table 2: Summary Statistics

Years	PDL	avg. MS	No. of Patents	No. of Semic. Patents
1989	29	0.77%	78,619	4,063
1990	43	0.72%	81,302	4,521
1991	99	0.77%	82,939	5,276
1992	99	0.65%	86,548	5,313
1993	96	0.66%	89,572	5,688
1994	112	0.66%	102,553	7,554
1995	64	0.57%	122,127	9,250
1996	33	0.64%	122,552	10,390
1997	42	0.56%	143,109	13,507

Table 2 presents the annual averages of relevant variables in our study. Sources: Thompson Financial, Gartner, Inc. and the U.S. Patent and Trademark Office.

Table 3: The PDL, R&D Investment and Patent Data

	PDL_{it}^S	rd_{it}	P_{it}	P_{it}^S
Mean	0.14	3.17	8.84	4.86
Std.Dev.	0.35	2.07	40.62	22.83
Median	0	2.77	0	0
Minimum	0	-4.61	0	0
Maximum	38	8.61	660	306
Proportion of zeros	90%	0%	90%	90%
Time Series	1989-1997	1989-1997	1976-1997	1976-1997

Table 3 presents the summary statistics of the most important variables in our study. Sources: Thompson Financial, Inc., Moody's and the U.S. Patent and Trademark Office.

Table 4: Path Dependency in R&D Investments

Variables	rd_{it}	rd_{it}
rd_{it-1}	0.89** (0.01)	0.79** (0.30)
rd_{it-2}		0.19** (0.37)
r_t^S	0.28** (0.09)	0.21** (0.10)
PDL_{it-1}^S	-0.02** (0.004)	-0.01** (0.003)
$Firms_t^S$	-0.002 (0.002)	-0.0007 (0.003)
Number of observations	396	305
Number of groups	91	83
Number of periods	4	4
Sargan test ($Prob > chi2$)	0.98	0.92
Arellano-Bond test ($Prob > z$)	0.24	0.51

Table 4 shows the estimation results for equations 1 and 2. The GMM estimator by Arellano and Bond (1991) is applied. We use internal and external instruments for the lagged dependent variable and PDL as described in the text. The adjusted standard errors (Windmeijer, 2005) are shown in the parenthesis. ** refers to a 1% significance level. Sources: Thompson Financial, Inc., Moody's and the U.S. Patent and Trademark Office.

Table 5: Impact of PDL on Patents

Vars.	P_{it}^S	P_{it}^S	P_{it}^S	P_{it}	P_{it}	P_{it}
Depend.						
Var_{it-1}	0.59** (0.02)	0.61 (0.01)	0.59 (0.003)	0.56 (0.03)	0.50 (0.01)	0.44 (0.01)
PDL_{it-1}^S	-0.07** (0.004)	-0.05 (0.002)	-0.05 (0.001)	-0.04 (0.005)	-0.02 (0.001)	-0.03 (0.001)
SARGAN/P	30.53/0.25	46.34/0.38	71.18/0.13	33.69/0.14	54.03/0.14	71.18/0.13

N=3,249, NT=22,743.

Table 5 shows the estimation results for the equations 7 and 8. As instruments we use lagged patents, lagged PDL, lagged market shares, lagged number of firms in technology and the pre-sample mean of the dependent variable. We use different lags in the set of our instrument variables. Standard errors are shown in parentheses, and calculated using the asymptotic variance of the two-step GMM estimator. Note that all estimates are significant at the 1% significance level. Sources: Thompson Financial, Inc., Moody's and the U.S. Patent and Trademark Office.

Table 6: Impact on Patents with and without PDL

Year	Obs. No Patents	Pred. No Patents	Pred. No Patents w/o PDL
1990	4,521	4,196	4,347
1991	5,276	6,715	6,932
1992	5,313	7,919	8,468
1993	5,688	8,610	9,381
1994	7,554	9,077	9,923
1995	9,250	9,246	10,246
1996	10,390	9,527	10,438
1997	13,507	9,884	10,551
Sum	61,499	65,174	70,286

Table 6 shows the impact on patents with and without PDL. Sources: Thompson Financial, Inc. and the U.S. Patent and Trademark Office.

Table 7: Impact of PDL on Revenues

<i>Variables</i>	R_{it}^S
R_{it-1}^S	0.69** (0.03)
PDL_{it-1}^S	-90.79** (18.24)
P_{it}^S	0.19** (0.04)
Ms_{it}^S	9.21** (0.43)
R_t^S	0.04** (0.01)
$Firms_t^S$	-24.38** (6.90)
<i>Time</i>	YES**
Number of observations	436
Number of groups	96
Number of periods	5
Sargan test ($Prob > chi2$)	0.42
Arellano-Bond test ($Prob > z$)	0.26

Table 7 reports the estimation results for the impact of PDLs on revenues as shown in equation (16). We apply the GMM estimator by Arellano-Bond (1991) is used. Robust standard errors (Windmeijer, 2005) are reported in parentheses. The p-values for the Sargan test and the Arellano-Bond autocorrelation test are presented at the bottom of the tables.** refers to a 1% significance level. Sources: Thompson Financial, Gartner, Inc. and the U.S. Patent and Trademark Office.