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# SBIR, Startups, and Subsequent Technological Development: Laser diodes in the United States and Japan


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# SBIR, Startups, and Subsequent Technological Development: Laser diodes in the United States and Japan*

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Abstract

How does the existence or absence of employee startups influence the patterns of subsequent technological development? By studying the development of laser diode technology in the U.S. and Japan at both the inventor and organizational levels using the difference-in-differences approach, this study empirically examines the impact of opportunities for startups promoted by SBIR in the U.S. on the technological trajectory of existing technology. According to the estimation results, an increase in employee startups promoted by SBIR could impede the subsequent development of the current technology earlier and cause it to stagnate at a lower level than what could have been achieved with no employee startups (as seen in Japan). This implies that the cumulative effects of technological development could vanish if R&D personnel strategically exit their parent firms to target different submarkets.

Keywords: Startups, Innovation, SBIR, Submarkets, R&D, Cumulative Technological Development, Japan–U.S. Comparison
JEL classification: O31 O32 O33 O38



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# 1. Introduction

Do employee startups promote innovation? This study explores whether the rise of opportunities to launch employee startups drives technological change. Using difference-in-differences (DID) estimation to study the development of laser diode technology in the U.S. and Japan, this study empirically examines the impact of employee startups promoted by the Small Business Innovation Research (SBIR) in the U.S. on the technological trajectory of existing technology.

Employee startups have played a vital role in industries, especially technology-intensive industries. These startups have emerged from parent firms' internal resources to be marketed separately and generate additional value (Klepper and Sleeper 2005, Franco and Filson 2006, Agarwal et al. 2007). A notable example is Fairchild Semiconductor and its spin-off/spin-out firms in Silicon Valley (Saxenian 1990a, 1990b). Employee startups and their supporting institutions, such as financing for startups, knowledge hubs, and flexible labor markets, have attracted considerable attention as factors that promote innovation. Since the early 2000s, many policies have been implemented to promote venture businesses and employee startups (Lundvall and Borrás 2005, Motohashi 2005, Park 2014).

However, do they promote innovation? Earlier literature on technological development and the history of technology has discussed that cumulative technological development plays a critical role in increasing the level of technology, making it suitable for industrial use (Abernathy 1978, Rosenberg and Trajtenberg 2004). How does the emergence of employee startups influence the level of cumulative technological development? Typically, incumbent firms improve the technology of existing products (Tushman and Anderson 1986, Christensen 1993). If employees leave the incumbents and start or join a startup, this would hinder the level of cumulative technological development of the incumbent firms. Some case studies have indicated that a flexible system of transactions, which promotes employee startups, could retard cumulative technological development (R.L. Florida and Kenney 1990, Numagami 1996, Shimizu 2019), although no empirical studies have comprehensively examined such effects.

It is challenging to empirically examine how the emergence of employee startups affects the trajectory of technology. For empirical analysis, we need samples that meet the following three conditions. First, we need a country/region that has witnessed rise in employee startups and a country/region that has not. This is because when policy intervention stimulates employee startups, the influence can be at the country/regional level. Second, those countries/regions were on a similar technological trajectory before the policy that led to a rise in employee startups was implemented in a country. Those countries/regions should not have any significant differences other than the fact that a startup support system was introduced. For example, if one of the countries had advanced in technological development than the other, it would be difficult to determine the effects of policy intervention because the difference in technological development itself could have changed the trajectory. This point related to the parallel trend assumption of the DID analysis. The third point is related to causal inference. The intervention is ideally exogenous. For example, this point is crucial when we conduct a randomized controlled trial (RCT). The subjects in RCTs are divided into two groups: treatment and control. The treatment group (also called the experimental group) receives the researcher-focused treatment. The subjects would be randomly allocated to one of these groups to enable statistical control over the intervention. As RCTs help in examining the causal relationship between the treatment and the effects, social scientists use them in several settings, such as in development economics (Banerjee et al. 2016), education (D.T. Campbell and Stanley 2015), health service (Cochrane 1972), and moral hazards in health insurance (Manning and Marquis 1996). However, as the RCT setting is not well maintained in social sciences, exogenous shocks to subjects such as earthquakes, terrorist attacks, and Napoleon's invasion, which is considered to randomly divide subjects into two groups, have been examined as a natural experiment (Acemoglu et al. 2011, Baker and Bloom 2013, Hikichi et al. 2017).

Given these conditions, we examine inventors and their organizations committed to laser diode R&D in the U.S. and Japan. The section titled "Laser Diodes, SBIR, and Technology Development" discusses how laser diode R&D in the U.S. and Japan meets these requirements. This study also shows that policies that encourage employee startups stifle subsequent technological development on a given technological trajectory. Although employee startups have attracted attention from different fields, such as entrepreneurship, regional clusters, and industry dynamics, few studies have empirically analyzed the impact of employee startups on subsequent technological development. As literature review shows that it can be assumed that a parent firm's productivity can reduce if skilled personnel leave and launch startups because the core source of a firm's competitive advantage in a knowledge-intensive industry is strongly embodied in its employees' human capital. Thus, a society that witnesses a high level of employee entrepreneurship and spin-offs may have technological development patterns that differ from that in which entrepreneurial spin-outs are rarely observed.

## 2. Previous Literature

This study attempts to bridge the gap in the literature on employee startups and that on innovation patterns. Employee startups have been examined from various perspectives, such as entrepreneurship, regional clusters, and knowledge spillovers.[1] Studies on employee startups have focused on identifying entrepreneurs (Begley and Boyd 1987, Crant 1996) and locating employee startups (Garvin 1983, A.C. Cooper 1985, Saxenian 1994), the initial market focus of employee startups (Anton and Yao 1995, Wiggins 1995, Klepper and Sleeper 2005), the relationships between employee startups and their parent firms, and the differences in the performance of employee startups (Agarwal et al. 2004, B.A. Campbell et al. 2012).

Previous literature on the relationship between employee startups (particularly spin-outs) and their parent organizations has observed that conflicts between the startup's founder and the parent firm may have existed on the formation of the employee startup (Klepper and Thompson 2010, Thompson and Chen 2011). An employee who

[1] Employee startups can be classified into two categories: spin-offs and spin-outs. The former applies when the employee startup has capital investment from its parent firm, which is a type of divestiture. The latter is when the employee startup does not have any capital ties with its parent company; this study focuses on this type. Due to the lack of information, much of the previous literature on employee startups has not classified them into these two categories. For a detailed literature review of employee startups, see Klepper (2001).

plans to spin out tends to transfer as many tangible and intangible assets as possible (e.g., his/her specific expertise and interpersonal networks) to the new workplace (Agarwal and Audretsch 2001). The parent firm also suffers adverse effects because the firm's capable human resources exit and move to employee startups (B.A. Campbell et al. 2012). The extent of the negative impact resulting from the loss of talented personnel from the parent firm depends on the firm's ability to find replacements with similar skills and other relevant attributes in the labor market or nurture such personnel internally. When firm-specific skills, tacit knowledge, or special expertise are crucial and the pool of talented personnel is limited in the labor market, a firm generally needs time to regain these human resources (Collins and Harrison 1975, Nonaka and Takeuchi 1995, Coff 1997, Zucker et al. 1998). Studies on startups in Silicon Valley and observations of employee startups have shown that talented personnel contribute greatly to knowledge spillovers and high-tech clustering. In contrast, they might also delay the ongoing R&D projects of their parent organizations (R.L. Florida and Kenney 1990).

Another line of argument regarding the relationship between a parent organization and its employee startups has suggested that employee startups influence the subsequent development of existing technology. Most literature indicate that employee startups initially tend to target a new submarket to avoid directly challenging their parent firm (Christensen 1993, Anton and Yao 1995, Wiggins 1995, Klepper 1996, Buenstorf and Klepper 2010). Submarkets appeal to different users and require production knowledge and methods that differ from existing markets (Buenstorf and Klepper 2010). Submarkets are areas where new entrants can launch their own businesses using existing technology. By leveraging the valuable discoveries and expertise that a founder has accumulated at an incumbent firm, employee startups in a high-tech industry typically target untapped markets (Klepper 2001, 2006, Bhaskarabhatla and Klepper 2014). This means that the increase in the number of employee startups can distribute resources from existing R&D projects to different submarkets (Shimizu 2019). In other words, studies suggest that the rise of employee startups could influence the trajectory of technological change, which has not yet been empirically examined.

While studies on employee startups have not examined the pattern of technological change, it has been an important research stream in the literature on the development of technology. The literature on economic history has repeatedly shown that the level of subsequent technological development drives the extent to which a technology's potential is realized (Rosenberg 1979, Mokyr 1990, Allen 2009). Because newly invented technology is usually rough and nascent, its subsequent cumulative development plays a crucial role in the full realization of its potential (Rosenberg 1979). Subsequent cumulative technological development is crucial for highly versatile technology, otherwise known as general-purpose technology (GPT). Electricity, steam engines, lasers, and artificial intelligence are generally regarded as typical examples of GPTs. GPTs have received attention because the occasional arrival of a new GPT yields large positive externalities for industrial growth and macroeconomic outcomes (Helpman 1998, Lipsey et al. 1998, Lipsey et al. 2005). A GPT initially has much scope for improvement, is eventually widely used, and has many technological complementarities (Lipsey et al. 1998). Therefore, the initial impact of GPTs on overall productivity growth is minimal. Recognizing the potential of highly versatile technology requires subsequent technological development. Specifically, the degree to which the basic technology that defines its fundamental performance plays a critical role in realizing the potential of highly versatile technology (Arthur 2009). For example, if the steam engine's thermal efficiency had not been developed and remained low, steam engines would not have been widely used as a source of energy (Mokyr 1990, 2002).

The pattern of subsequent technological development has been discussed in two different research streams: one based on the concepts of paradigms and trajectories and other on management studies vis-à-vis the dominant design. Thomas Kuhn introduced the concept of paradigms to explain the pattern of development in science (Kuhn 1962). A paradigm is loosely defined as a distinct pattern of finding, reasoning, and problem-solving in science and technology. Based on Kuhn's discussion of paradigms, Dosi introduced a technological trajectory defined as "a cluster of possible technological directions whose boundaries are defined by the nature of the paradigm itself" (Dosi 1982, p. 154). Specifically, the paradigm defines the direction of subsequent technological advances. Once a certain technological trajectory emerges, it sets the direction for subsequent technological development (Constant 1980, Dosi 1982, Mackenzie 1990). Technological trajectories are created by multiple actors. Similar to the normal science paradigm described by Kuhn (1962), technological trajectories emerge through interactions among several actors; that is, a certain technological trajectory emerges when most actors take a cumulative technological approach to the same technological problem.

The other research stream involves management studies in terms of the concept of dominant design. Dominant design is a key technological feature that has become a de facto industry standard. It determines the direction(s) of subsequent technological development (Utterback and Abernathy 1975, Abernathy 1978, Suárez 2004). Interpretations of the concepts, underlying causal mechanisms, and units of analysis vary in existing empirical literature on dominant design (Murmann and Frenken 2006). However, most studies show reveals that several new designs and various new materials are created before dominant design emerges. After the emergence of a dominant design, subsequent technological development becomes incremental, cumulative, and standardized.

Although the research fields and terminologies do not entirely match, both research streams suggest that subsequent cumulative technological development will reduce if most actors do not invest their resources in the same technological problems with the same technological approach. Moreover, while the extant literature on technological trajectories and dominant design has generally described the pattern of technological development, it has not articulated how the pattern varies according to the rise of employee startups. Building on the existing work on employee startups and innovation patterns, this study examines how employee startups influence the technological trajectory of subsequent technological development by closely examining laser diodes. Studies on employee startups and technological innovation (R.L. Florida and Kenney 1990) have shown that the subsequent development of the existing technology is adversely affected when submarkets are highly cultivated by entrepreneurial employee startups. Therefore, this study examines whether the rise of employee startups delays the level of subsequent development of basic technology.

Bhaskarabhatla and Klepper (2014) explored a similar theme in their paper. They studied the U.S. laser industry from the 1960s to the early 21st century and found that the emergence of submarkets, which are usually developed by employee startups, can fundamentally alter an industry's market structure and the character of innovation. As they described industrial evolution in terms of submarkets by exploring lasers, their paper provides significant insights for this study. The unit of analysis here is much smaller than in this comparative study. To elaborate, Bhaskarabhatla and Klepper (2014) combined different types of lasers, such as $CO_2$, He–Ne, ion, gas, ruby, dye, solid state, and laser diodes, and considered them a single industry. However, the performance specifications of these lasers are fairly diverse (Dupuis 2004, Coleman et al. 2012). Many lasers are not technically similar to each other. For example, ruby lasers, which first became operational worldwide in 1960, and laser diodes, also called semiconductor lasers, which were invented in 1962, are not closely related in terms of their technologies and application markets, although they share much in fundamental physics. Different types of lasers are used in completely different and independent markets, such as compact disk players, missile tracking, welding, and inertial confinement fusion. This means that their potential for substitution is fairly limited. Therefore, if we consider all lasers as a single industry and each type of laser and its applications as a submarket, we may overestimate the role of submarkets developed by startups in industry evolution. Therefore, this study focuses on laser diodes and their applications. This allows us to discuss how inventors utilize their knowledge in submarkets that are closely related to laser diode technology.

## 3. Laser Diodes, SBIR, and Technological Developments

Lasers are generally considered to belong to the class of versatile technologies. Among the many varieties of laser (e.g., $CO_2$, YAG, He–Ne, ruby, and laser diodes), laser diodes are the most widely sold and used globally. Laser diodes are typically used in telecommunications, optical information storage, sensors, pointers, displays, measurements, and medical applications; they are also used for pumping other lasers. Laser diode was one of the most important technologies underpinning the dramatic changes that occurred in information technology in the latter half of the twentieth century.

R&D in laser diodes in the U.S. and Japan allows for an empirical study of how the increase in employee startups affects the trajectory of technology for three reasons. As explained earlier, we need two societies because when the policy that led to the rise of employee startups is implemented, the influence can be at the country level. One is a society in which the rise of employee startups has been observed and the other is one in which no rise of employee startups has been observed. If we only consider societies with institutions that encourage spin-outs, we cannot distinguish whether subsequent technological development has been reduced by spin-outs or by technological maturity because we have nothing to compare with; therefore, this study compares the U.S. and Japan. Both countries had the same level of technological maturity; however, the U.S. implemented a system to promote spin-outs. In the laser diode industry, numerous startups were founded after 1982 in. the U.S., whereas they were virtually absent in Japan (Forrest et al. 1996).

Second, these countries were on a similar technological trajectory before the policy intervention that led to surge in employee startups implemented in the U.S. Earlier studies on laser diode technology have shown that U.S. and Japanese incumbent firms have been the main actors throughout the history of laser diode research (Agrawal 1995, Forrest et al. 1996, Yoshikuni 2009). Throughout the 1960s and 1970s, U.S. firms, such as Bell Laboratories, RCA, GE, IBM, Xerox, and HP, and Japanese firms, such as NTT, Hitachi, NEC, Fujitsu, and Sony, targeted the same markets, faced the same technological problems and aimed to achieve the same goals (Ikegami and Matsukura 2000, Dupuis 2004). Scientists and engineers in the U.S. and Japan competed to develop technologies that determined the fundamental performance of laser diodes, such as operating lifetime, reliability, and wavelength. However, U.S. scientists and engineers began to diverge from their Japanese counterparts in the 1980s, when they began to leave their parent organizations to launch startups.

There were a large number of employee startups in the field of laser diodes in the U.S. Most startups emerged in the mid-1980s (Olsen 2009, Shimizu 2010). The only exception was Laser Diode Laboratories, launched in 1967, which was a spin-out from RCA. The rest of the startups were launched from the mid-1980s onward. Startup foundations were promoted by SBIR.

SBIR, a competitive award-based program launched in 1982, was designed to encourage small businesses to engage in federal research/research and development (R/R&D) with the potential for commercialization. As SBIR has provided opportunities, including further R&D and commercialization, by awarding funding, it has a significant impact not only on the SBIR recipients but also on the scientists/engineers and managers who are yet to be awarded funding but are interested in pursuing future opportunities provided by SBIR. In total, 1,403 projects were awarded by the SBIR for laser diode research between 1982 and 2018. As some firms received SBIR awards successively, a simple aggregation of the number of projects awarded each year can lead to an overestimation. Therefore, firms awarded multiple times were identified and counted as a single entity to avoid overestimating the number of firms awarded funding. In total, 420 firms received awards between 1982 and 2018. This figure captures only firms receiving SBIR awards. Therefore, the number of startups shown in this technological field is, in fact, a modest estimation.

SBIR has been examined from different perspectives, such as its purpose and performance (Audretsch et al. 2002, Audretsch 2003, R.S. Cooper 2003), long-term effects (Lerner 1996), entrepreneurial risk (Link and Scott 2010), and multidimensionality (Lanahan and Feldman 2015). Although the negative impact of SBIR has been observed on university spin-offs in digital technology(Fini et al. 2023), many studies on SBIR have concurred that SBIR stimulated R&D and its commercialization (Lerner 1996, Audretsch et al. 2002, Audretsch 2003, Link and Scott 2010). While previous literature has explored the extent to which SBIR increased its commercialization, it has not considered the counterfactual situation that would have occurred if SBIR were not implemented. However, by examining the award recipients of the SBIR program at the NASA Langley Research Center, Archibald and Finifter (2003) showed that the recipients experienced a reduction in basic research along with increased commercial success, whereas the project experienced higher rates of commercial success (Archibald and Finifter 2003). A similar pattern was observed in another study. Toole and Czarnitzki examined university spin-offs from 1994 to 2004 and found that SBIR led to the nontrivial impact of the academic brain drain from academic research to commercialization and reduced knowledge accumulation in academics (Toole and Czarnitzki 2007, 2010).

While many employee startups emerged in the laser diode industry in the U.S., such startups were virtually nonexistent in Japan (Japan Development Bank 1986, Ikegami and Matsukura 2000). Examining the laser diode and optoelectronics industry in the U.S. and Japan, the industrial report highlighted the following:

> Due to the vibrant entrepreneurial industry base that is an integral part of the U.S. economy, and which is apparently nearly absent in Japan, numerous small companies have spun-off from their larger, parent companies. (Forrest et al. 1996, p. xvii)

The rise of startups in the U.S., which were largely promoted by SBIR, and the virtual absence of such startups in Japan provides a excellent opportunity for conducting quasi-natural experiments. This is because organizations in both countries were competing to solve the same technical problem in the same technological field, resulting in development of the same technological trajectory.

Regarding the difference in employee startups between the U.S. and Japan, studies have explored the factors that promoted startups in the U.S., such as entrepreneurship, the growth of venture capital, the knowledge pool, and networks (Dore 1986, R. Florida and Kenney 1988, Bygrave and Timmons 1992, P.A. Gompers, 1994; Saxenian, 1994; Kaplan, 1995; Kenney, 2000; Paul A. Gompers et al. 2010). The rarity of startups in Japan has been explained by the less-developed venture capital system, well-developed in-house labor market, seniority-based pay, assumption of lifetime employment, and poor conditions for reemployment (Aoki and Dore 1994, Itoh 1994). Opportunities for launching employee startups were limited in Japan. Although it is still interesting to explore how this difference emerged over time, the important point for this study lies in empirically investigating how the existence or absence of employee startups influences the pattern of subsequent technological development, given the difference in the occurrence of spin-outs between the U.S. and Japan.

The U.S. employee startups targeted customized and untapped submarkets, such as those for short-distance communications, sensors, and optical pumping, using basic laser diode technology. However, such startups were virtually absent in Japan, and Japanese incumbent firms continued to compete in the same technological areas (Forrest et al. 1996, Shimizu 2010, 2019).

One might suppose that the reason why untapped markets began to develop in the U.S. during the mid-1980s is that U.S. firms matured technologically before Japanese firms in the life cycle of technology. However, since the mid-1970s, U.S. and Japanese firms have been fiercely competing in R&D over improving the reliability and extending the longevity of laser diodes, along with laser oscillation with new materials, which continued into the 1980s (Dupuis 2004). Lasers began to be used in their primary applications, such as optical communications and DVD pickups, only in the 1990s. Fundamental technologies, such as the highly reliable DFB laser, the basis of today's optical communications, and the blue semiconductor laser, the technical basis for the blue LED that won the Nobel Prize in Physics in 2014, were born in the 1990s and later (Nakamura et al. 2000). There is no evidence that laser diode technology was already mature in the 1980s, or that only the U.S. firms had already matured technology.

SBIR was created to strengthen the role of innovation in R&D by small firms. The fact that this objective was justified and that SBIR was institutionalized does not in itself mean that this policy intervention is exogenous to innovation. However, since the SBIR was not exclusively for laser diode technology, the development of laser diode technology did not affect the timing of the SBIR implementation. As described earlier, after SBIR was introduced, numerous startups were established in the laser diode industry, while such startups were virtually absent in Japan. Therefore, using this context with the DID approach, this study derives an appropriate counterfactual to estimate the causal effect of the increase in employee startups on technological change.

## 4. Estimation Strategy and Data

Because our study focuses on the effects of treatment (the rise of opportunities for employee startups), a statistical challenge is to show that the differences in technological trajectory can be attributed to the treatment alone. Therefore, using the DID approach, this study conducts a quasi-natural experiment to derive an appropriate counterfactual to estimate the causal effect of the rise of employee startups on technological change (Bertrand et al. 2004, Abadie 2005, Smith and Todd 2005). Specifically, given that SBIR provided funding opportunities and stimulated the rise of employee startups, this study examines how the opportunity to establish startups offered by SBIR influenced the subsequent development of basic technology, determining the technical performance of the technology, from which other technologies are derived.

We examine how the opportunities created by SBIRs have influenced technology trajectories at the level of two different units of analysis: inventor and organizational. Regarding the extent of inventor level, the opportunities provided by SBIRs are expected to influence inventors. Specifically, it is likely to influence the inventor's choice of R&D projects, such as whether to continue existing R&D or laterally utilize knowledge for new R&D projects. The second unit of analysis is at the organizational level. It can be assumed that the opportunities provided by SBIR also influence the organizations' R&D projects. The inventors conduct R&D in the organization; thus, this study focuses on inventor-level analysis. However, because R&D projects are usually conducted as a division of labor in an organization, the R&D project selection is the result of organizational decision-making. Moreover, organizational level analysis is also important for examining whether SBIR has an impact on both new entrants and incumbents.

We identify basic technology using International Patent Classification (IPC) number, H01S5. First , H01 is the number given to basic electrical elements. H01S5 is specifically the technology classified as basic electric elements of laser diodes (also called semiconductor lasers). H01S5 is ascribed to technology specifically related to laser diodes, such as structure, processes, apparatus for excitation, and arrangements for controlling the laser output parameters, including operating longevity, reliability, and wavelength. H01S5 was recognized as an important basic technology, which is an important basis for subsequent use of laser diodes (Japan Patent Office 1998). Concretely, we construct the following dummy variable. We give one to a patent with a primary IPC code of H01S5, which is precisely defined as a basic laser diode technology. We assign 0 to a laser diode patent whose primary IPC is not H01S5. This is a conservative measurement for basic technology. Because the estimation using patents with a primary IPC of H01S5 might be too narrow in scope, we construct another dummy variable by running the same exercise with it as a robustness check. We assign one to patents for which H01S5 is included in the IPC, and we assign 0 to the rest of the laser patents.

Counting the value of the former dummy variable for each inventor in a given year gives us an outcome variable *Number of Basic Patent Primary* at the inventor level. Counting the value of the same dummy variable for each patent assignee in a given year redefines the outcome variable at the organizational level. Analogously, counting the value of the latter dummy variable for each inventor in a given year facilitates another outcome variable referred to as *Number of Basic Patent Included* at the inventor level. Counting the value of the same dummy for each assignee in a given year redefines the outcome variable at the organizational level. In sum, we obtain four outcome variables: two each for the inventor-level analysis and the organizational-level analysis. *Number of Basic Patent Primary* is the number of patents with a primary IPC of H01S5 obtained by an inventor or organization in a given year. *The Number of Basic Patent Included* is the number of patents an inventor or organization obtained in a given year where H01S5 was included in the IPC. *Number of Basic Patent Included* counts the number of basic laser diode patents more broadly than *Number of Basic Patent Primary*.

For each outcome variable denoted by $y$, we assume that $y$ has an exponential conditional mean function given by

$$\mathrm{E}[y|X, Post\ Period, Country, Interaction\ Term] = \exp\left(X\beta_1 + \beta_2 Post\ Period + \beta_3 Country + \beta_4 Interaction\ Term\right).$$

Here, *Post Period* is a dummy variable assuming a value of 1 if the application year of the patent concerned is a given cutoff year or later and 0 otherwise. We use two different cutoff years, 1982 and 1984, because it is reasonable to consider the possibility that SBIR influences scientists' and engineers' R&D activities with a lag. *Country* is a dummy variable taking one if the assignee is located in the U.S., where SBIR was introduced in 1982; otherwise, 0. *Interaction Term* is the product of *Post Period* and *Country. X* is a vector containing control variables and a constant.

At the inventor level, the control variables are *Incumbent*, *University*, *Cumulative Number of Basic Patents*, *Latest Number of Laser Diode Patents*, *H-index*, *Top 1%*, *Unemployment*, and *GDP per Capita Growth*. *Incumbent* is a dummy variable taking the value 1 if an organization had already patented in the field before 1984. University is a dummy variable that has the value one if the organization to which the inventor belongs is an academic or public research institution, otherwise 0. The inventor's affiliation is identified by the patent assignee. If the patent has more than one assignee, the inventor's affiliation is identified in the following two steps. First, we check the assignees of other patents acquired by the inventor of the patent in question. If the inventor's organization cannot be identified in the first step, the inventor's name is checked in the papers published in *Applied Physics Letters* and *Electronics Letters*, which are the most widely published journals in this field, to identify the inventor's affiliation. If the inventor has multiple affiliations with an academic/public institution and a firm, the *University* dummy variable is assigned 1 for the inventor because the inventor's R&D is likely to be more basic than that of a firm's inventor. *Cumulative Number of Basic Patents* is the number of patents obtained by the inventor or organization before the patent in question being applied for. *Latest Number* of *Laser Diode Patents* is the log-transformed number of laser diode patents that the inventor obtained in a given year. *H-index* and *Top 1%* are explained below.. *Unemployment* is the unemployment rate of the year in which the patent concerned applied in the assignee's country. *GDP per Capita Growth* is an analogous counterpart to the GDP growth rate. *Unemployment* and *GDP* are introduced to control for macroeconomic environments.

*H-index* and *Top 1%* are introduced to analyze inventor's ability. Studies on scientists' preferences for technological research have shown that scientists and inventors tend to choose the area of R&D based on their past R&D performance. Therefore, scientists must accumulate knowledge about existing art in the field and field-specific learning and problem-solving skills (Cohen and Levinthal 1990). Newcomers to the field lack fundamental understanding and basic skills needed in the field and need time to reach the technological frontier (Jones 2009). Thus, experienced scientists with significant research performance are less likely to change their area of research than those who have not achieved such significant research performance, even when they move to another organization (Jones 2009, Arts and Fleming 2018). Therefore, employers usually expect such high-performing scientists and engineers to continue to work in their fields rather than explore other fields. However, some employers may want to recruit high-performing scientists and engineers to actively explore submarkets. Furthermore, the presence of extremely high-performing scientists would also enhance the firm's reputation, making it easier to raise funds and recruit new scientists and engineers. Therefore, this study uses a squared term for high-performing researchers and confirms the nonlinear relationship. This study uses h-index, which was invented to assess scholars' performance by measuring both the number and quality of works to identify high-performing inventors (Hirsch 2005). We count the number of patents obtained by inventors in the field of laser diodes and their citations and derive the h-index for all inventors. We refer to it as *H-index*. *Top 1%* is a dummy variable taking the value one if the related inventor is among the top 1% in terms of their h-index. If inventors who have the same h-index as the top 1% of inventors, this study does not differentiate between inventors with the same h-index but draws a line at the next h-index number.

At the organizational level, the control variables are *Incumbent*, *University*, *Cumulative Number of Basic Patents*, *Latest Number of Laser Diode Patents*, *Unemployment* and *GDP*. While the definitions of *Incumbent, Unemployment,* and *GDP* are identical to those at the inventor level, the definitions of the remaining variables are similar to those at the inventor level. *University* is a dummy variable that takes a value of 1 if the organization is an academic or a public research institution. *Cumulative Number of Basic Patents* is the number of patents obtained by concerned patent assignee before the concerned patent application year. *Latest Number of Laser Diode Patents* is the log-transformed number of laser diode patents that the patent assignee obtained in a given year. Table 1 presents a summary of the variables for reference.

<Insert Table 1>

Regarding the distribution of $y$, we first consider the Poisson density function to conduct the Poisson regression analysis, a well-known count-data regression analysis, for our baseline analysis. We then consider the negative binomial (NB) density function to conduct the NB regression analysis and check the robustness of the baseline analysis results.

Of particular interest in the regression analysis is the treatment effect of SBIR opportunities on the outcome variables. Similar to many other nonlinear DID models and contrary to the linear DID model, the treatment effect is not equal to the interaction-term coefficient in the Poisson and NB DID models, $\beta_4$ in our model. Among several (often cumbersome) methods for capturing the treatment effect in nonlinear DID models in the literature (Ai and Norton 2003, Athey and Imbens 2006, Greene 2010, Puhani 2012, Leitgöb 2014), we adopt the difference-in-semi-elasticities (DIS) estimator developed by Shang, Nesson, and Fan (2018) for nonlinear DID models with exponential conditional mean functions including the Poisson and NB DID models and provide a straightforward interpretation of the treatment effect that follows (Shang et al. 2018).

The DIS estimator to be obtained in our specification is

$$DIS = [\exp(\beta_2 + \beta_4) - 1] - [\exp(\beta_4) - 1] \ .$$

Here, the first term is the percentage change in the number of patents obtained by an inventor or organization due to the introduction of SBIR in the U.S. and the second term is the Japanese counterpart. We refer to these as semi-elasticity in the U.S. and Japan, respectively. Subtracting the semi-elasticity in Japan from that in the U.S., the DIS estimator is interpreted as stating that the number of patents obtained by an inventor or organization in the U.S. increases by SBIR compared with that in Japan by $100 \times DIS$ percentage points (ppt). For example, if the semi-elasticity in the U.S is $-0.2$ and in Japan it is $-0.05$, the resulting DIS estimate is $-0.15$, which can be interpreted as the number of patents obtained by an inventor or organization in the U.S. decreases by SBIR in comparison to that in Japan by 15 ppt. As such, the DIS estimator allows us to interpret the interaction effect in terms of semi-elasticity, which is analogous to the semi-elasticity interpretations of other coefficients, $\beta_1$, $\beta_2$, and $\beta_3$ in our model. Hence, a positive (negative) DIS estimate is interpreted as indicating that SBIR has had a positive (negative) impact on the development of basic technology at the innovator or organizational level, while a zero DIS estimate is interpreted as indicating that it has not.

Patents are the primary data source for this study. Not all technological developments are covered by patents because not all technologies are patentable; moreover, a firm might decide to strategically hide its invention(s) (Griliches 1990, Jaffe and Trajtenberg 2002). However, patents have been widely used to examine technological change in a particular area of technology or industry because they provide important information, such as the inventors' name, the name and address of the assignee, a technological description, and the date of application.

This study uses two different patent sources: patents granted by the United States Patent and Trademark Office (USPTO) and Japan Patent Office (JPO). Specifically, we use USPTO and JPO patents to examine R&D activities by inventors affiliated with U.S. and Japanese organizations, respectively. Then, we estimate the impact of SBIR on R&D in the U.S. relative to Japan. These two datasets are combined because analyzing patent data of one of the two countries may underestimate the R&D of startups in the other country. Companies file patents in the countries in which they conduct business. Therefore, companies not intending to expand overseas will not file patents in foreign countries. If many startups are not interested in expanding business overseas in the early stages of their growth, then analyzing patents in one of the countries may underestimate the startup's R&D. If only U.S. patents were used for analysis, it could underestimate the R&D of Japanese startups and SMEs and overestimate that of U.S. startups. The opposite is true if only Japanese patents are used. R&D conducted in the U.S. and Japan can be easily examined using patent data from third countries, this underestimates the R&D of startups and SMEs in both countries. Therefore, in this study, we use patents from the U.S. Patent Office for R&D of U.S. organizations and patents from the Japanese Patent Office for R&D of Japanese organizations. As explained earlier, this study investigates whether there is a difference between Japan and the U.S. in the change in the semi-elasticity of basic R&D outcomes before and after introducing a system to promote startups (SBIR). Therefore, there is no technical problem in analyzing the R&D outcomes of Japanese organizations using Japanese patents those of U.S. organizations using U.S. patents. However, for a robustness check, the same analysis is also conducted using only the patent granted by the USPTO.

We collect the patents granted from 1958, when the first patent was issued for laser diodes, to 2010 through a keyword search for laser diodes, semiconductor lasers, or semiconductor lasers in either the patent title or the abstract. At both the inventor-level and organizational-level analyses, the sample period of our datasets is from 1958 to 2010. Besides analyzing the dataset of the full sample period, we analyze the datasets of the subsample period for a robustness check. By checking the assignee's address, we identify patents granted by U.S. or Japanese organizations. Patents are categorized into technological classifications using IPC codes. This study uses IPC codes to identify laser diode technologies, as explained earlier.

## 5. Empirical Results

Tables 2 and 3 report the descriptive statistics of the variables and their correlation matrix for inventor- level analysis with USPTO and JPO patent data.

<Insert Table 2 and 3>

Table 4 presented the results of the inventor-level analysis using USPTO and JPO data. Model 1 is the baseline model. Models 2 to 13 use different sets of control variables (Models 2 to 6), different regression methods (Models 7 and 8), a different outcome variable (Models 9), different cutoff years (Models 10 and 11), or different data sampling periods (Models 12 to 13) to check for the robustness of the results in Model 1. In all these models, the treatment effect of SBIR opportunities on the outcome variable is of particular interest. Following Shang, Nesson, and Fan (2018), we compared with the value of the DIS estimator, which is obtained by subtracting the semi-elasticities in Japan from the U.S. counterpart. Table 4 also reports the estimated values of $\beta$'s and the sample size and calculated pseudo R-squared and log pseudo-likelihood with robust standard errors in parentheses. Each estimated value of $\beta$ is interpreted as the semi-elasticity of the outcome variable with respect to the explanatory or control variable concerned, except for that of $\beta_4$.

<Insert Table 4>

In all models, the estimation results show that SBIR treatment has a negative impact on the subsequent development of laser diode base technology at a statistically significant level of 1%. The reported DIS estimates vary from −0.258 to −0.383, which implies that, compared with Japan, where employee startups virtually nonexistent, the opportunities offered by SBIR reduced the number of basic laser diode patents by an inventor more in the U.S. by 25.8 to 38.3 ppt. This is because the number of laser diode basic patents has been decreased in the U.S. by 32.7 to 54.8 ppt while it has been decreased by at most 17.4 ppt or not been significantly decreased in Japan.

Considering the results on the control variables, the coefficients of all the control variables except *Unemployment* and *New Entrant* are statistically significant and positive in many models. They suggest that inventors at universities, who score highly on the h-index, have obtained many basic patents in the past, or have obtained many laser diode patents recently are more likely to patent basic technology and that inventors are more likely to patent basic technology in the period of economic expansion. The results on the coefficient of *Unemployment* are unstable. As expected, the results that the coefficients of *New Entrant* are negative in all models and that the coefficient values are large, ranging from -0.318 to -0.5, means that new entrants have lower levels of basic R&D, as expected. Furthermore, even after controlling for the effect of new entrants, the results showing a negative DIS indicate that the effect of SBIR on reducing basic research extends to inventors in incumbent firms.

In all models, the coefficient of *H-index* is positive and that of its squared term is negative, indicating a nonlinear relationship between top inventors and non-high-performing inventors shifting from basic research. Although the coefficient of the squared term is much smaller than that of *H-index*, so the effect of being a very top inventor on the shift from basic research is marginal, this result indicates that the degree of the shift from basic research varies according to the inventor. Models 3 and 4 use a dummy for the top 1% and top 10% of high-performing scientists, respectively, instead of *H-index*. The results are consistent with the models using *H-index*.

All models except Models 7 and 8 are estimated using Poisson regression under the assumption that $y$ is conditionally distributed according to the Poisson density function. Models 7 and 8 are estimated using two variants of the NB regression, referred to as NB1 and NB2, under the assumption that the conditional distribution of $y$ is the NB density function. The NB regression model typically includes the Poisson model as a special case by relaxing the Poisson model's equidispersion (equality of mean and variance) property. Specifically, in the NB model, the variance of $y$ is given by $(\text{mean}) + \alpha(\text{mean})^p$, with $p = 1$ for NB1 and $p = 2$ for NB2 (Cameron and Trivedi 2013). Parameter $\alpha$ is called the overdispersion parameter, because if $\alpha = 0$, the variance is equal to the mean, whereas if $\alpha > 0$, the variance exceeds the mean, implying that the Poisson model underestimates the data dispersion. Accordingly, we must check whether $\alpha > 0$ is observed and the robustness of the results from the Poisson model in that case.

The log-transformed value of *Log Alpha* represents the result of the overdispersion $\alpha$ in Models 7 and 8. In both models, it is observed to be statistically significant and negative at the 1% level with −0.459 and −1.492, implying $\alpha$ being 0.632 and 0.225 and not equal to zero. This implies that the Poisson model (Models 1–3 and 6 and 14) underestimates the dispersion of the outcome. A comparison with log pseudo-likelihood implies that the NB2 model is reasonable. However, most estimation results, including the SBIR treatment effect, are robust to the choice of regression model.

Models 10 and 11 use different cutoff years of 1982 and 1983, and the DIS estimate is similar to that in Model 1.

Models 12 and 13 analyze subsample datasets in which the sample periods end in 1993 (10 years from 1984) and 2003 (20 years from 1984), respectively. We have two reasons for doing so: one is that the sample period from 1958 to 2010 might be too long to examine the effect of SBIR with the DID design because conditions might have changed since the SBIR was introduced. The other reason is that the effect of SBIR on the subsequent technological development of the existing technology might change as time evolves after the introduction of SBIR. On the one hand, the impact of SBIR might diminish over time. On the other hand, the impact of SBIR might be increasing because supporting institutions were established after the SBIR was introduced. While networking among scientists and engineers grows and venture capitalists begin to evaluate the SBIR-awarded project highly, launching a startup becomes an increasingly realistic option for scientists and engineers as such institutions develop. In both Models 12 and 13, the DIS estimate remains significantly positive at the 1% level, indicating that the introduction of SBIR reduced the invention of basic technology.

Next, let us look at the impact of SBIR at the organizational level. Since the SBIR is a system that encourages spin-outs, its direct impact will be on researchers who conduct R&D. However, the opportunities provided by the SBIR would also have an impact on the organization's R&D selection. The analysis at the organizational level is essentially the same exercise as at the inventor level.

<Insert Table 5 and 6>

Table 5 shows the descriptive statistics of the organizational-level analysis using the USPTO and JPO data, and Table 6 shows the correlation matrix.

<Insert Table 7>

Table 7 shows the result of the organizational-level analysis using USPTO and JPO data. The results are consistent with those of the inventor-level analysis. The reported DIS estimates vary from −0.274 to −0.394, which indicates that the opportunities provided by SBIR reduce the number of basic laser diode patents by an organization more in the U.S. than in Japan by 27.4 to 39.4 ppt. This result shows that the SBIR implementation reduced basic R&D in both individual and organizational levels, indicating that incentives for individual inventors and entrepreneurs have changed in the U.S. and firms, in turn, are changing their R&D targets.

Next, as a robustness check, we analyze the results using the USPTO data alone, while considering that when only the USPTO data are used, Japanese organizations that did not have a patent in the U.S. are not included in the data.

<Insert Table 8, 9, and 10>

Table 8 shows the descriptive statistics of the inventor-level analysis using the USPTO data alone, and Table 9 shows the correlation matrix. Table 10 shows the results of the inventor-level analysis using USPTO data alone. This differs from the earlier analysis in that the USPTO is also used to analyze Japanese firms. This empirical result is consistent with Table 4 although we should be cautious in comparing the coefficients because of different data being used.

<Insert Table 11, 12, and 13>

Table 11 shows the descriptive statistics of the organizational-level analysis using the USPTO data alone, and Table 12 shows the correlation matrix. Table 13 reports the results of the organizational-level analysis using the USPTO data only. The basic models of our analysis, Models 1 through 7, show consistent estimation results with previous analyses using USPTO and JPO data. However, the DIS estimation is somewhat unstable for Model 8, which uses NB1, and Model 9, which broadly defines the basic patent.

## 6. Conclusions

This study examines whether the rise of opportunities to launch employee startups drives technological change. Empirical analyses show that the opportunities provided by SBIR designed to promote R&D and its commercialization affected the trajectory of basic laser diode technology. Earlier studies have indicated that progress on the technological trajectory is likely to retain some cumulative features, which will gradually increase productivity (Kuhn 1962, Rosenberg 1979, Dosi 1982). This study showed that the cumulative features of technological development gradually disappeared due to the surge in employee startups promoted by SBIR in the U.S. The divergence from the R&D of the basic laser diode structure is one sign that the U.S. inventors have shifted their focus from R&D to other fields in submarkets that startups have attempted to enter.

This study assesses the impact of SBIR on both the inventor and the organizational. The empirical results at the organizational level were also consistent with the inventor estimates, showing the SBIR had shifted U.S. firms' focus on R&D from basic to applied. The increased focus on applied R&D was more pronounced among new entrant firms, consistent with earlier literature, indicating that spin-out firms utilize knowledge produced at their parental organizations and target untapped markets (Agarwal et al. 2004, B.A. Campbell et al. 2012).

The study findings suggest the possibility that SBIR channeled inventors to reduce their level of R&D efforts in basic technology and rush into commercialization. Many scientists engaged in R&D are leaving their parent firms to use their accumulated technological knowledge laterally and to launch startups targeting an untapped submarket. If the supply of skilled scientists is abundant, this trend does not have a significant impact on subsequent technological development because incumbent firms can immediately hire new scientists to fill the vacancies created by spin-outs. However, the pool of skilled scientists is not instantly increased as skilled scientists are highly knowledgeable. Professional R&D experience in a laboratory and formal graduate-level education in physics are the prerequisites for a scientist to be will be deemed skilled in this domain. As submarkets with high expected returns are not infinite but rather limited, scientists/engineers must rush to a preferred submarket. The fiercer the competition to fill untapped submarkets, the earlier the spin-out. If most scientists engaged in R&D disengage from trajectory-oriented activities to utilize technology laterally and launch a startup, this will eventually hamper the technological trajectory.

Employee startups, which utilize the existing technology laterally and shift R&D to individual submarkets can lead to earlier fade out of the technological trajectory and remain at a lower level than if no entrepreneurial spin-out had occurred.

The estimation results are consistent with previous literature examining various funding sources and innovation in the U.S. and with the finding that the association with U.S. government funding, NIH research, and SBIR grants hindered technical innovation (Pahnke et al. 2015). The study findings also explain why Japanese firms were good imitators and achieved great process innovations, whereas U.S. firms were successful in terms of product innovation but were poor imitators (Rosenberg 1988). A general explanation for this observation is entrepreneurship and cultural differences. However, the study findings suggest that institutional factors promoting employee startups play an important role in establishing or hampering technological trajectories to promote subsequent cumulative technological development.

One might suppose that it is reasonable that basic research in the U.S. was reduced because SBIR encourages the commercialization of R&D results by startups. Indeed, an increase in applied development research is naturally expected due to the impact of SBIR. However, the decline in basic research is not the intended result of SBIR. The SBIR's reduction in basic technology development has been confirmed even after controlling for new entrants and thus extends to researchers who were conducting R&D in incumbent firms. This is an unintended consequence of the change in the incentives for inventors provided by SBIR. Furthermore, SBIR's impact may still be considered positive because SBIR has certainly stimulated commercialization from basic technological development although it has delayed subsequent development of basic technology. It can be assumed that some submarkets would grow significantly and develop into important markets. Moreover, if many scientists continue to engage in R&D along the existing technological trajectory, the aggregate amount of R&D investment in this area will gradually increase. Increasing R&D investment in the existing technological trajectory, on the one hand, reduces the potential for technological breakthroughs and lowers the profitability of firms, on the other. Therefore, we must consider resource allocation in both basic research and its development/commercialization to fully evaluate the impact on innovation of employee startups developed by SBIR, which is an important point for future research.

However, as basic R&D was nascent when SBIR was introduced (Ikegami and Matsukura 2000, Dupuis 2004), Japanese firms held a large share of the global market for laser diodes since the mid-1980s (Forrest et al. 1996, Wood and Brown 1998). They developed blue lasers based on R&D in basic technologies such as material structure. This process led to the development of white LEDs, which won the Nobel Prize in Physics in 2014 and opened up a huge market (Nakamura et al. 2000), considered to represent the opportunity costs to shift R&D from basic to applied research at an earlier stage was significant.

As the study findings are based on our field observations, caution must be exercised about generalizations. Moreover, other factors not explored in this study could explain the observed patterns. A classic explanation might be that Japanese firms tended to have advantages in incremental process innovations, whereas U.S. firms tended to allocate more resources to radical and revolutionary product innovations. One could attribute this difference to the cultural differences between the U.S. and Japan. This explanation assumes that the U.S. culture prefers revolutionary innovation, while the

Japanese culture prefers cumulative innovation. However, if this explanation is correct, the trajectories would have diverged even before SBIR was introduced. As this study focuses on longitudinal scrutiny of the laser diode industry and a discussion of the different patterns of innovation between the U.S. and Japan, and owing to space limitations, we have not explored other examples. However, detailed and longitudinal studies in future research could unravel the mechanisms through which the different patterns emerge and provide useful comparisons to offer a better understanding of the patterns of subsequent technological development.

**Table 1: Description of Variables**

| Variables | Description |
|---|---|
| No. of Basic Patent Primary | Number of patents with a primary IPC of H01S5 for an inventor/organization obtained in a given year |
| No. of Basic Patent Included | Number of patents an inventor/organization obtained where H01S5 is included in the IPC |
| Post Period | 1 if the patent concerned is applied in a given treatment year (1982, 1983, or 1984) or later; otherwise, 0 |
| Country | 1 if the assignee is located in the U.S.; otherwise, 0 |
| Interaction Term | Product of Post period and Country |
| Incumbent | 1 if an organization had already patented in the field before 1984; otherwise, 0 |
| University | 1 if assignee is a university; otherwise, 0 |
| H-index | H-index of the inventor |
| H-index_Squared | Squared term of the H-index |
| Top 1% | 1 if the inventor concerned is among the top 1% inventors in terms of the H-index, otherwise 0 |
| Top 10% | 1 if the inventor concerned is among the top 10% inventors in terms of the H-index; otherwise, 0 |
| Cumulative Number of Basic Patents | Number of patents obtained from the inventor before the concerned patent application year |
| Latest Number of Laser Diode Patents | Log-transformed number of laser diode patents that the inventor obtained in a given year |
| Unemployment | Unemployment rate in the year when the patent concerned applied in the assignee's country |
| GDP | GDP per capita growth rate in the year when the patent concerned applied in the assignee's country |

**Table 2: Descriptive Statistics for USPTO and JPO Inventor Level**

| | Variable | Obs | Mean | Std. dev. | Min | Max |
|---|---|---|---|---|---|---|
| 1 | No. of Basic Patent Primary | 36,240 | 0.334 | 0.764 | 0 | 17 |
| 2 | No. of Basic Patent Included | 36,240 | 0.641 | 1.197 | 0 | 66 |
| 3 | Country | 36,240 | 0.430 | 0.495 | 0 | 1 |
| 4 | Post Period 82 | 36,240 | 0.965 | 0.184 | 0 | 1 |
| 5 | Interaction 82 | 36,240 | 0.418 | 0.493 | 0 | 1 |
| 6 | Post Period 83 | 36,240 | 0.954 | 0.210 | 0 | 1 |
| 7 | Interaction 83 | 36,240 | 0.415 | 0.493 | 0 | 1 |
| 8 | Post Period 84 | 36,240 | 0.941 | 0.235 | 0 | 1 |
| 9 | Interaction 84 | 36,240 | 0.413 | 0.492 | 0 | 1 |
| 10 | New Entrant | 36,240 | 0.427 | 0.495 | 0 | 1 |
| 11 | Top 1% | 36,240 | 0.065 | 0.246 | 0 | 1 |
| 12 | Top 10% | 36,240 | 0.307 | 0.461 | 0 | 1 |
| 13 | Hindex | 36,240 | 1.836 | 2.912 | 0 | 44 |
| 14 | Hindex Squared | 36,240 | 11.850 | 64.201 | 0 | 1936 |
| 15 | University | 36,240 | 0.059 | 0.236 | 0 | 1 |
| 16 | Cumulative Number of Basic Patents | 36,240 | 0.950 | 3.578 | 0 | 59 |
| 17 | Latest Number of Laser Diode Patents | 36,240 | 0.233 | 0.451 | 0 | 4.431 |
| 18 | Unemployment | 36,240 | 4.500 | 1.719 | 1.2 | 9.708 |
| 19 | GDP per Capita Growth | 36,240 | 1.660 | 1.804 | -5.370 | 6.911 |

**Table 3: Correlation Matrix USPTO and JPO Inventor Level**

| | Variable | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | No. of Basic Patent Primary | | | | | | | | | | | | | | | | | | |
| 2 | No. of Basic Patent Included | 0.640 | | | | | | | | | | | | | | | | | |
| 3 | Country | -0.156 | -0.122 | | | | | | | | | | | | | | | | |
| 4 | Post Period 82 | -0.027 | -0.034 | 0.037 | | | | | | | | | | | | | | | |
| 5 | Interaction 82 | -0.157 | -0.124 | 0.976 | 0.162 | | | | | | | | | | | | | | |
| 6 | Post Period 83 | -0.032 | -0.037 | 0.053 | 0.868 | 0.161 | | | | | | | | | | | | | |
| 7 | Interaction 83 | -0.157 | -0.124 | 0.971 | 0.161 | 0.995 | 0.186 | | | | | | | | | | | | |
| 8 | Post Period 84 | -0.042 | -0.043 | 0.070 | 0.765 | 0.166 | 0.882 | 0.187 | | | | | | | | | | | |
| 9 | Interaction 84 | -0.158 | -0.125 | 0.966 | 0.160 | 0.989 | 0.185 | 0.995 | 0.209 | | | | | | | | | | |
| 10 | New Entrant | -0.163 | -0.138 | 0.479 | 0.165 | 0.501 | 0.190 | 0.506 | 0.215 | 0.511 | | | | | | | | | |
| 11 | Top 1% | 0.167 | 0.249 | 0.040 | 0.019 | 0.042 | 0.016 | 0.041 | 0.017 | 0.040 | -0.016 | | | | | | | | |
| 12 | Top 10% | 0.206 | 0.250 | 0.048 | 0.006 | 0.053 | 0.007 | 0.053 | 0.008 | 0.053 | -0.045 | 0.395 | | | | | | | |
| 13 | Hindex | 0.174 | 0.270 | -0.071 | 0.017 | -0.059 | 0.018 | -0.057 | 0.019 | -0.055 | -0.083 | 0.629 | 0.568 | | | | | | |
| 14 | Hindex Squared | 0.052 | 0.162 | 0.082 | 0.020 | 0.086 | 0.022 | 0.087 | 0.025 | 0.088 | 0.023 | 0.455 | 0.252 | 0.828 | | | | | |
| 15 | University | -0.023 | -0.031 | 0.108 | 0.019 | 0.111 | -0.002 | 0.110 | -0.019 | 0.110 | 0.096 | -0.039 | -0.026 | -0.059 | -0.027 | | | | |
| 16 | Cumulative Number of Basic Patents | 0.355 | 0.286 | -0.135 | 0.035 | -0.130 | 0.038 | -0.129 | 0.040 | -0.128 | -0.127 | 0.334 | 0.301 | 0.377 | 0.241 | -0.039 | | | |
| 17 | Latest Number of Laser Diode Patents | 0.393 | 0.516 | 0.031 | 0.026 | 0.040 | 0.024 | 0.041 | 0.016 | 0.043 | 0.007 | 0.309 | 0.333 | 0.343 | 0.228 | -0.048 | 0.173 | | |
| 18 | Unemployment | -0.131 | -0.122 | 0.660 | 0.120 | 0.640 | 0.120 | 0.624 | 0.125 | 0.608 | 0.337 | 0.006 | -0.008 | -0.095 | 0.025 | 0.077 | -0.097 | 0.026 | |
| 19 | GDP per Capita Growth | 0.064 | 0.056 | -0.040 | -0.115 | -0.047 | -0.084 | -0.033 | -0.084 | -0.038 | -0.091 | 0.007 | 0.022 | 0.018 | 0.005 | -0.004 | -0.002 | -0.018 | -0.311 |

**Table 4: Estimation Results at USPTO and JPO Inventor Level**

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Poisson | Poisson | Poisson | Poisson | Poisson | Poisson | NB2 | NB1 | Poisson | Poisson | Poisson | Poisson | Poisson |
| | 1984 | 1984 | 1984 | 1984 | 1984 | 1984 | 1984 | 1984 | 1984 | 1982 | 1983 | 1984 | 1984 |
| | Primary | Primary | Primary | Primary | Primary | Primary | Primary | Primary | Primary Included | Primary | Primary | Primary | Primary |
| Variables | Full | Full | Full | Full | Full | Full | Full | Full | Full | Full | Full | Until 1993 | Until 2003 |
| Post Period | -0.191*** | -0.108** | -0.109** | -0.112** | -0.106** | -0.116*** | -0.158*** | -0.138*** | -0.0909*** | -0.0459 | -0.0575 | -0.0677 | -0.0995** |
| | (0.0463) | (0.0464) | (0.0461) | (0.0454) | (0.0464) | (0.0446) | (0.0376) | (0.0427) | (0.0289) | (0.0481) | (0.0445) | (0.0499) | (0.0451) |
| Country | -0.0686 | -0.108 | -0.121 | -0.119 | -0.0962 | 0.0966 | 0.0559 | 0.123 | 0.332*** | 0.123 | 0.153* | 0.116 | 0.480*** |
| | (0.0922) | (0.0924) | (0.0917) | (0.0899) | (0.0926) | (0.0912) | (0.0822) | (0.0911) | (0.0605) | (0.0976) | (0.0923) | (0.157) | (0.0955) |
| Interaction | -0.605*** | -0.340*** | -0.351*** | -0.423*** | -0.372*** | -0.466*** | -0.413*** | -0.490*** | -0.473*** | -0.487*** | -0.521*** | -0.328*** | -0.508*** |
| | (0.0869) | (0.0871) | (0.0862) | (0.0848) | (0.0875) | (0.0853) | (0.0775) | (0.0879) | (0.0556) | (0.0943) | (0.0882) | (0.0911) | (0.0858) |
| University | 0.0444 | 0.0990** | 0.115** | 0.134*** | 0.113** | 0.145*** | 0.175*** | 0.164*** | 0.0412 | 0.155*** | 0.152*** | 0.212** | 0.186*** |
| | (0.0478) | (0.0479) | (0.0476) | (0.0468) | (0.0479) | (0.0468) | (0.0449) | (0.0463) | (0.0331) | (0.0469) | (0.0470) | (0.0828) | (0.0507) |
| Cumulative Number of Basic Patents | 0.0613*** | 0.0590*** | 0.0528*** | 0.0470*** | 0.0563*** | 0.0474*** | 0.0677*** | 0.0471*** | 0.0343*** | 0.0472*** | 0.0472*** | 0.0326*** | 0.0457*** |
| | (0.00187) | (0.00187) | (0.00201) | (0.00175) | (0.00198) | (0.00185) | (0.00332) | (0.00119) | (0.00159) | (0.00184) | (0.00184) | (0.00304) | (0.00189) |
| Latest Number of Laser Diode Patents | 0.0734*** | 0.0754*** | 0.0703*** | 0.0684*** | 0.0681*** | 0.0894*** | 0.251*** | 0.0849*** | 0.0880*** | 0.0894*** | 0.0894*** | 0.246*** | 0.0851*** |
| | (0.00909) | (0.00917) | (0.00912) | (0.00874) | (0.00958) | (0.00949) | (0.0159) | (0.00209) | (0.00526) | (0.00948) | (0.00948) | (0.0182) | (0.0104) |
| Unemployment | -0.0317*** | -0.0240** | -0.0232** | -0.0104 | -0.0205* | -0.0129 | -0.000696 | -0.0115 | -0.0437*** | -0.0102 | -0.0118 | 0.0147 | -0.0822*** |
| | (0.0114) | (0.0114) | (0.0113) | (0.0109) | (0.0113) | (0.0109) | (0.00957) | (0.00924) | (0.00729) | (0.0107) | (0.0108) | (0.0250) | (0.0130) |
| GDP per Capita Growth | 0.0675*** | 0.0611*** | 0.0621*** | 0.0602*** | 0.0614*** | 0.0623*** | 0.0501*** | 0.0627*** | 0.0401*** | 0.0628*** | 0.0636*** | 0.0484*** | 0.0738*** |
| | (0.00744) | (0.00731) | (0.00727) | (0.00711) | (0.00728) | (0.00709) | (0.00636) | (0.00598) | (0.00447) | (0.00712) | (0.00710) | (0.00854) | (0.00738) |
| New Entrant | | -0.500*** | -0.494*** | -0.437*** | -0.499*** | -0.447*** | -0.425*** | -0.464*** | -0.318*** | -0.466*** | -0.458*** | -0.393*** | -0.380*** |
| | | (0.0298) | (0.0295) | (0.0299) | (0.0297) | (0.0299) | (0.0270) | (0.0276) | (0.0208) | (0.0297) | (0.0298) | (0.0580) | (0.0338) |
| Top 1% | | | 0.366*** | | | | | | | | | | |
| | | | (0.0511) | | | | | | | | | | |
| Top 10% | | | | 0.624*** | | | | | | | | | |
| | | | | (0.0249) | | | | | | | | | |
| Hindex | | | | | 0.0184*** | 0.165*** | 0.106*** | 0.165*** | 0.164*** | 0.165*** | 0.165*** | 0.201*** | 0.189*** |

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | (0.00447) | (0.0112) | (0.0125) | (0.00682) | (0.00979) | (0.0112) | (0.0112) | (0.0309) | (0.0123) |
| Hindex Squared | | | | | | -0.00722*** | -0.00566*** | -0.00765*** | -0.00562*** | -0.00720*** | -0.00721*** | -0.00886*** | -0.00786*** |
| | | | | | | (0.000986) | (0.000893) | (0.000427) | (0.000667) | (0.000985) | (0.000986) | (0.00302) | (0.00102) |
| Log Alpha | | | | | | | -0.459*** | -1.492*** | | | | | |
| | | | | | | | (0.0585) | (0.0552) | | | | | |
| Constant | -0.939*** | -0.946*** | -0.961*** | -1.213*** | -0.983*** | -1.324*** | -1.540*** | -1.286*** | -0.611*** | -1.392*** | -1.381*** | -1.732*** | -1.257*** |
| | (0.0578) | (0.0575) | (0.0568) | (0.0566) | (0.0576) | (0.0598) | (0.0523) | (0.0511) | (0.0412) | (0.0632) | (0.0601) | (0.0836) | (0.0624) |
| Semielasticity in the United States | -0.548*** | -0.361*** | -0.369*** | -0.414*** | -0.380*** | -0.441*** | -0.435*** | -0.466*** | -0.431*** | -0.413*** | -0.439*** | -0.327*** | -0.455*** |
| | (0.0316) | (0.0456) | (0.0444) | (0.0405) | (0.0445) | (0.0393) | (0.0372) | (0.0404) | (0.0263) | (0.0474) | (0.0419) | (0.0518) | (0.0389) |
| Semielasticity in Japan | -0.174*** | -0.103** | -0.104** | -0.106*** | -0.100** | -0.109*** | -0.146*** | -0.129*** | -0.0869*** | -0.0449 | -0.0559 | -0.0655 | -0.0947** |
| | (0.0382) | (0.0417) | (0.0413) | (0.0406) | (0.0417) | (0.0397) | (0.0321) | (0.0372) | (0.0264) | (0.0459) | (0.0420) | (0.0467) | (0.0408) |
| DIS | -0.375*** | -0.258*** | -0.265*** | -0.308*** | -0.280*** | -0.332*** | -0.289*** | -0.337*** | -0.344*** | -0.368*** | -0.383*** | -0.261*** | -0.361*** |
| | (0.0515) | (0.0633) | (0.0623) | (0.0589) | (0.0626) | (0.0574) | (0.0504) | (0.0556) | (0.0381) | (0.0662) | (0.0603) | (0.0692) | (0.0574) |
| Observations | 36,240 | 36,240 | 36,240 | 36,240 | 36,240 | 36,240 | 36,240 | 36,240 | 36,240 | 36,240 | 36,240 | 11,490 | 26,867 |
| Pseudo R2 | 0.104 | 0.111 | 0.114 | 0.128 | 0.112 | 0.129 | 0.111 | 0.0898 | 0.144 | 0.129 | 0.129 | 0.208 | 0.127 |
| Log pseudolikelihood | -25734 | -25526 | -25458 | -25042 | -25504 | -25009 | -24131 | -24700 | -35708 | -25024 | -25017 | -8983 | -19358 |

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

**Table 5: Descriptive Statistics at the USPTO and JPO Organization Level**

| | Variable | Obs | Mean | Std. dev. | Min | Max |
|---|---|---|---|---|---|---|
| 1 | No. of Basic Patent Primary | 6,704 | 0.791 | 2.454 | 0 | 40 |
| 2 | No. of Basic Patent Included | 6,704 | 1.487 | 4.089 | 0 | 67 |
| 3 | Country | 6,723 | 0.581 | 0.493 | 0 | 1 |
| 4 | Post Period 82 | 6,704 | 0.953 | 0.213 | 0 | 1 |
| 5 | Interaction 82 | 6,704 | 0.558 | 0.497 | 0 | 1 |
| 6 | Post Period 83 | 6,704 | 0.941 | 0.236 | 0 | 1 |
| 7 | Interaction 83 | 6,704 | 0.553 | 0.497 | 0 | 1 |
| 8 | Post Period 84 | 6,704 | 0.930 | 0.254 | 0 | 1 |
| 9 | Interaction 84 | 6,704 | 0.550 | 0.498 | 0 | 1 |
| 10 | New Entrant | 6,704 | 0.734 | 0.442 | 0 | 1 |
| 11 | University | 6,704 | 0.090 | 0.286 | 0 | 1 |
| 12 | Cumulative Number of Basic Patents | 6,704 | 9.479 | 38.103 | 0 | 531 |
| 13 | Latest Number of Laser Diode Patents | 6,704 | 0.607 | 0.876 | 0 | 4.564 |
| 14 | Unemployment | 6,723 | 4.845 | 1.774 | 1.100 | 9.708 |
| 15 | GDP per Capita Growth | 6,723 | 1.614 | 1.921 | -5.370 | 12.162 |

**Table 6: Correlation Matrix USPTO and JPO Organizational Level**

| | Variable | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | No. of Basic Patent Primary | | | | | | | | | | | | | | |
| 2 | No. of Basic Patent Included | 0.913 | | | | | | | | | | | | | |
| 3 | Country | -0.224 | -0.225 | | | | | | | | | | | | |
| 4 | Post Period 82 | -0.040 | -0.051 | 0.038 | | | | | | | | | | | |
| 5 | Interaction 82 | -0.218 | -0.219 | 0.953 | 0.251 | | | | | | | | | | |
| 6 | Post Period 83 | -0.042 | -0.050 | 0.054 | 0.891 | 0.243 | | | | | | | | | |
| 7 | Interaction 83 | -0.217 | -0.218 | 0.945 | 0.248 | 0.991 | 0.279 | | | | | | | | |
| 8 | Post Period 84 | -0.047 | -0.055 | 0.072 | 0.816 | 0.246 | 0.917 | 0.278 | | | | | | | |
| 9 | Interaction 84 | -0.217 | -0.217 | 0.938 | 0.247 | 0.984 | 0.277 | 0.993 | 0.302 | | | | | | |
| 10 | New Entrant | -0.318 | -0.328 | 0.188 | 0.371 | 0.266 | 0.417 | 0.281 | 0.421 | 0.287 | | | | | |
| 11 | University | -0.044 | -0.047 | -0.012 | -0.014 | -0.007 | -0.021 | -0.008 | -0.017 | -0.008 | -0.035 | | | | |
| 12 | Cumulative Number of Basic Patents | 0.625 | 0.610 | -0.223 | 0.031 | -0.212 | 0.035 | -0.210 | 0.036 | -0.209 | -0.334 | -0.051 | | | |
| 13 | Latest Number of Laser Diode Patents | 0.653 | 0.713 | -0.191 | -0.020 | -0.176 | -0.022 | -0.174 | -0.032 | -0.174 | -0.429 | -0.072 | 0.493 | | |
| 14 | Unemployment | -0.170 | -0.178 | 0.646 | 0.124 | 0.612 | 0.105 | 0.586 | 0.101 | 0.568 | 0.149 | -0.013 | -0.102 | -0.126 | |
| 15 | GDP per Capita Growth | 0.060 | 0.062 | -0.042 | -0.159 | -0.055 | -0.111 | -0.034 | -0.115 | -0.040 | -0.110 | 0.029 | -0.047 | 0.027 | -0.325 |

**Table 7: Estimation Results at USPTO and JPO Organization Level**

| Variables | 1<br>Poisson<br>1984<br>Primary<br>Full | 2<br>Poisson<br>1984<br>Primary<br>Full | 3<br>NB2<br>1984<br>Primary<br>Full | 4<br>NB1<br>1984<br>Primary<br>Full | 5<br>Poisson<br>1984<br>Primary Included<br>Full | 6<br>Poisson<br>1982<br>Primary<br>Full | 7<br>Poisson<br>1983<br>Primary<br>Full | 8<br>Poisson<br>1984<br>Primary<br>1993 | 9<br>Poisson<br>1984<br>Primary<br>2003 |
|---|---|---|---|---|---|---|---|---|---|
| Post Period | -0.241*** | -0.234*** | -0.225*** | -0.250*** | -0.267*** | -0.264*** | -0.269*** | -0.158** | -0.219*** |
| | (0.0644) | (0.0672) | (0.0731) | (0.0681) | (0.0422) | (0.0778) | (0.0713) | (0.0748) | (0.0694) |
| Country | 0.325** | 0.319** | 0.435*** | 0.369*** | 0.452*** | 0.210 | 0.259* | 0.339* | 0.532*** |
| | (0.129) | (0.131) | (0.133) | (0.139) | (0.0865) | (0.136) | (0.133) | (0.201) | (0.142) |
| Interaction | -0.696*** | -0.684*** | -0.676*** | -0.697*** | -0.635*** | -0.579*** | -0.630*** | -0.388*** | -0.574*** |
| | (0.115) | (0.119) | (0.121) | (0.133) | (0.0756) | (0.128) | (0.124) | (0.130) | (0.121) |
| University | 0.290*** | 0.289*** | 0.362*** | 0.339*** | 0.300*** | 0.292*** | 0.289*** | 0.432*** | 0.333*** |
| | (0.0685) | (0.0686) | (0.0709) | (0.0736) | (0.0418) | (0.0691) | (0.0686) | (0.0903) | (0.0709) |
| Cumulative Number of Basic Patents | 0.00159*** | 0.00157*** | 0.00218*** | 0.00193*** | 0.000902*** | 0.00152*** | 0.00156*** | 0.000681 | 0.00126*** |
| | (0.000266) | (0.000266) | (0.000319) | (0.000187) | (0.000222) | (0.000263) | (0.000264) | (0.000495) | (0.000296) |
| Latest Number of Laser Diode Patents | 1.133*** | 1.129*** | 1.217*** | 1.066*** | 1.174*** | 1.124*** | 1.128*** | 1.181*** | 1.141*** |
| | (0.0243) | (0.0280) | (0.0232) | (0.0194) | (0.0211) | (0.0282) | (0.0282) | (0.0345) | (0.0343) |
| Unemployment | -0.0309 | -0.0307 | -0.0424** | -0.0382** | -0.0483*** | -0.0220 | -0.0237 | -0.0238 | -0.0725*** |
| | (0.0191) | (0.0191) | (0.0186) | (0.0159) | (0.0140) | (0.0194) | (0.0193) | (0.0356) | (0.0232) |
| GDP per Capita Growth | 0.0570*** | 0.0566*** | 0.0532*** | 0.0606*** | 0.0413*** | 0.0556*** | 0.0577*** | 0.0494*** | 0.0546*** |
| | (0.0124) | (0.0124) | (0.0122) | (0.0101) | (0.00846) | (0.0124) | (0.0124) | (0.0161) | (0.0133) |
| New entrant | | -0.0226 | -0.0512 | -0.0858* | 0.0900* | -0.0562 | -0.0330 | -0.0176 | 0.0157 |
| | | (0.0688) | (0.0560) | (0.0514) | (0.0473) | (0.0678) | (0.0685) | (0.0964) | (0.0745) |
| Log Aalpha | | | -0.875*** | -0.521*** | | | | | |
| | | | (0.100) | (0.0875) | | | | | |
| Constant | -1.483*** | -1.474*** | -1.623*** | -1.314*** | -0.850*** | -1.441*** | -1.457*** | -1.580*** | -1.407*** |
| | (0.0965) | (0.103) | (0.0961) | (0.0894) | (0.0714) | (0.111) | (0.106) | (0.125) | (0.116) |
| Semielasticity in the United States | -0.608*** | -0.601*** | -0.594*** | -0.612*** | -0.594*** | -0.569*** | -0.593*** | -0.421*** | -0.548*** |
| | (0.0355) | (0.0409) | (0.0406) | (0.0450) | (0.0271) | (0.0471) | (0.0442) | (0.0629) | (0.0468) |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Semielasticity in Japan | -0.214*** | -0.209*** | -0.202*** | -0.222*** | -0.235*** | -0.232*** | -0.236*** | -0.147** | -0.197*** |
| | (0.0506) | (0.0532) | (0.0584) | (0.0530) | (0.0323) | (0.0597) | (0.0544) | (0.0638) | (0.0557) |
| DIS | -0.394*** | -0.392*** | -0.392*** | -0.391*** | -0.360*** | -0.338*** | -0.357*** | -0.274*** | -0.351*** |
| | (0.0642) | (0.0649) | (0.0694) | (0.0686) | (0.0402) | (0.0725) | (0.0666) | (0.0880) | (0.0706) |
| Observations | 6,704 | 6,704 | 6,704 | 6,704 | 6,704 | 6,704 | 6,704 | 1,975 | 4,742 |
| Pseudo R2 | 0.561 | 0.561 | 0.262 | 0.248 | 0.622 | 0.560 | 0.561 | 0.594 | 0.561 |
| Log pseudolikelihood | -5377 | -5377 | -5129 | -5230 | -7312 | -5390 | -5381 | -1935 | -4104 |

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

**Table 8: Descriptive Statistics of the USPTO Inventor Level**

| | Variable | Obs | Mean | Std. dev. | Min | Max |
|---|---|---|---|---|---|---|
| 1 | No. of Basic Patent Primary | 33,336 | 0.319 | 0.876 | 0 | 30 |
| 2 | No. of Basic Patent Included | 33,336 | 0.654 | 1.379 | 0 | 66 |
| 3 | Country | 33,336 | 0.467 | 0.499 | 0 | 1 |
| 4 | Post Period 82 | 33,336 | 0.976 | 0.152 | 0 | 1 |
| 5 | Interaction 82 | 33,336 | 0.454 | 0.498 | 0 | 1 |
| 6 | Post Period 83 | 33,336 | 0.970 | 0.170 | 0 | 1 |
| 7 | Interaction 83 | 33,336 | 0.451 | 0.498 | 0 | 1 |
| 8 | Post Period 84 | 33,336 | 0.964 | 0.187 | 0 | 1 |
| 9 | Interaction 84 | 33,336 | 0.448 | 0.497 | 0 | 1 |
| 10 | New Entrant | 33,336 | 0.481 | 0.500 | 0 | 1 |
| 11 | Top 1% | 33,336 | 0.082 | 0.275 | 0 | 1 |
| 12 | Top 10% | 33,336 | 0.406 | 0.491 | 0 | 1 |
| 13 | Hindex | 33,336 | 1.823 | 3.583 | 0 | 44 |
| 14 | Hindex Squared | 33,336 | 16.162 | 73.215 | 0 | 1936 |
| 15 | University | 33,336 | 0.046 | 0.209 | 0 | 1 |
| 16 | Cumulative Number of Basic Patents | 33,336 | 0.842 | 3.218 | 0 | 52 |
| 17 | Latest Number of Laser Diode Patents | 33,336 | 0.294 | 0.486 | 0 | 4.431 |
| 18 | Unemployment | 32,813 | 4.832 | 1.629 | 1 | 10 |
| 19 | GDP per Capita Growth | 33,336 | 1.453 | 1.980 | -5.370 | 11.623 |

**Table 9: Correlation Matrix USPTO Inventor Level**

| | Variable | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | No. of Basic Patent Primary | | | | | | | | | | | | | | | | | | |
| 2 | No. of Basic Patent Included | 0.686 | | | | | | | | | | | | | | | | | |
| 3 | Country | -0.133 | -0.126 | | | | | | | | | | | | | | | | |
| 4 | Post Period 82 | -0.015 | -0.016 | -0.019 | | | | | | | | | | | | | | | |
| 5 | Interaction 82 | -0.134 | -0.128 | 0.974 | 0.146 | | | | | | | | | | | | | | |
| 6 | Post Period 83 | -0.014 | -0.017 | -0.019 | 0.893 | 0.129 | | | | | | | | | | | | | |
| 7 | Interaction 83 | -0.134 | -0.128 | 0.969 | 0.145 | 0.994 | 0.162 | | | | | | | | | | | | |
| 8 | Post Period 84 | -0.019 | -0.015 | -0.013 | 0.803 | 0.119 | 0.899 | 0.149 | | | | | | | | | | | |
| 9 | Interaction 84 | -0.135 | -0.128 | 0.963 | 0.144 | 0.988 | 0.161 | 0.994 | 0.179 | | | | | | | | | | |
| 10 | New Entrant | -0.112 | -0.091 | 0.406 | 0.153 | 0.432 | 0.171 | 0.438 | 0.191 | 0.444 | | | | | | | | | |
| 11 | Top 1% | 0.204 | 0.270 | -0.023 | 0.004 | -0.019 | -0.004 | -0.020 | -0.006 | -0.020 | -0.067 | | | | | | | | |
| 12 | Top 10% | 0.218 | 0.260 | -0.143 | 0.021 | -0.133 | 0.021 | -0.131 | 0.024 | -0.130 | -0.118 | 0.363 | | | | | | | |
| 13 | Hindex | 0.173 | 0.258 | -0.062 | 0.053 | -0.051 | 0.056 | -0.049 | 0.063 | -0.047 | -0.065 | 0.619 | 0.519 | | | | | | |
| 14 | Hindex Squared | 0.084 | 0.186 | 0.021 | 0.030 | 0.026 | 0.032 | 0.027 | 0.036 | 0.028 | -0.016 | 0.502 | 0.261 | 0.850 | | | | | |
| 15 | University | -0.020 | -0.036 | 0.189 | 0.020 | 0.191 | 0.014 | 0.190 | 0.017 | 0.190 | 0.094 | -0.042 | -0.036 | -0.046 | -0.030 | | | | |
| 16 | Cumulative Number of Basic Patents | 0.336 | 0.293 | -0.128 | 0.029 | -0.123 | 0.029 | -0.122 | 0.033 | -0.121 | -0.104 | 0.397 | 0.294 | 0.563 | 0.430 | -0.036 | | | |
| 17 | Latest Number of Laser Diode Patents | 0.398 | 0.521 | -0.094 | 0.060 | -0.082 | 0.065 | -0.080 | 0.072 | -0.078 | 0.005 | 0.289 | 0.316 | 0.324 | 0.241 | -0.051 | 0.202 | | |
| 18 | Unemployment | -0.066 | -0.059 | 0.634 | 0.057 | 0.612 | 0.027 | 0.593 | -0.001 | 0.575 | 0.264 | -0.032 | -0.085 | -0.016 | 0.012 | 0.128 | -0.071 | 0.058 | |
| 19 | GDP per Capita Growth | 0.011 | 0.011 | 0.085 | -0.098 | 0.075 | -0.059 | 0.088 | -0.071 | 0.083 | -0.040 | 0.019 | -0.008 | -0.034 | -0.005 | -0.001 | -0.013 | -0.086 | -0.245 |

**Table 10: Estimation Results at the USPTO Inventor Level**

| Variables | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Poisson | Poisson | Poisson | Poisson | Poisson | Poisson | NB2 | NB1 | Poisson | Poisson | Poisson | Poisson | Poisson |
| | 1984 | 1984 | 1984 | 1984 | 1984 | 1984 | 1984 | 1984 | 1984 | 1982 | 1983 | 1984 | 1984 |
| | Primary | Primary | Primary | Primary | Primary | Primary | Primary | Primary | Primary Included | Primary | Primary | Primary | Primary |
| | Full | Full | Full | Full | Full | Full | Full | Full | Full | Full | Full | Until 1993 | Until 2003 |
| Post Period | -0.337*** | -0.263*** | -0.262*** | -0.262*** | -0.246*** | -0.280*** | -0.300*** | -0.287*** | -0.225*** | -0.235*** | -0.188*** | -0.161*** | -0.240*** |
| | (0.0613) | (0.0612) | (0.0612) | (0.0602) | (0.0610) | (0.0600) | (0.0584) | (0.0664) | (0.0335) | (0.0777) | (0.0703) | (0.0587) | (0.0601) |
| Country | 0.157 | 0.131 | 0.130 | 0.204** | 0.148 | 0.204** | 0.243*** | 0.240** | 0.296*** | 0.175 | 0.255** | -0.243* | 0.191* |
| | (0.0992) | (0.0989) | (0.0988) | (0.0969) | (0.0985) | (0.0976) | (0.0940) | (0.104) | (0.0553) | (0.110) | (0.104) | (0.144) | (0.101) |
| Interaction | -0.736*** | -0.550*** | -0.550*** | -0.607*** | -0.522*** | -0.525*** | -0.472*** | -0.547*** | -0.531*** | -0.496*** | -0.577*** | -0.184* | -0.368*** |
| | (0.0915) | (0.0922) | (0.0922) | (0.0908) | (0.0925) | (0.0913) | (0.0886) | (0.101) | (0.0502) | (0.107) | (0.0996) | (0.0977) | (0.0914) |
| University | 0.380*** | 0.383*** | 0.384*** | 0.390*** | 0.352*** | 0.346*** | 0.348*** | 0.356*** | 0.112*** | 0.340*** | 0.342*** | 0.541*** | 0.360*** |
| | (0.0563) | (0.0562) | (0.0564) | (0.0561) | (0.0562) | (0.0560) | (0.0561) | (0.0565) | (0.0390) | (0.0560) | (0.0560) | (0.0940) | (0.0660) |
| Cumulative Number of Basic Patents | 0.0487*** | 0.0470*** | 0.0468*** | 0.0421*** | 0.0560*** | 0.0513*** | 0.0936*** | 0.0521*** | 0.0278*** | 0.0514*** | 0.0513*** | 0.0261*** | 0.0552*** |
| | (0.00263) | (0.00267) | (0.00303) | (0.00229) | (0.00416) | (0.00405) | (0.00494) | (0.00158) | (0.00242) | (0.00408) | (0.00407) | (0.00425) | (0.00356) |
| Latest Number of Laser Diode Patents | 1.081*** | 1.090*** | 1.088*** | 0.984*** | 1.144*** | 1.117*** | 1.124*** | 1.070*** | 1.118*** | 1.112*** | 1.114*** | 1.314*** | 1.129*** |
| | (0.0244) | (0.0241) | (0.0241) | (0.0255) | (0.0240) | (0.0245) | (0.0206) | (0.0153) | (0.0187) | (0.0245) | (0.0245) | (0.0318) | (0.0282) |
| Unemployment | -0.0376*** | -0.0335*** | -0.0332*** | -0.0256** | -0.0384*** | -0.0410*** | -0.0446*** | -0.0454*** | -0.0416*** | -0.0325*** | -0.0370*** | 0.0528** | -0.0371*** |
| | (0.0125) | (0.0124) | (0.0124) | (0.0118) | (0.0125) | (0.0124) | (0.0107) | (0.00976) | (0.00715) | (0.0124) | (0.0124) | (0.0213) | (0.0135) |
| GDP per Capita Growth | 0.0396*** | 0.0331*** | 0.0330*** | 0.0321*** | 0.0317*** | 0.0329*** | 0.0212*** | 0.0334*** | 0.0315*** | 0.0337*** | 0.0347*** | 0.0316*** | 0.0382*** |
| | (0.00766) | (0.00752) | (0.00751) | (0.00714) | (0.00813) | (0.00792) | (0.00617) | (0.00534) | (0.00413) | (0.00794) | (0.00792) | (0.00950) | (0.00876) |
| New Entrant | | -0.358*** | -0.357*** | -0.307*** | -0.364*** | -0.338*** | -0.322*** | -0.350*** | -0.181*** | -0.357*** | -0.349*** | -0.467*** | -0.284*** |
| | | (0.0297) | (0.0297) | (0.0299) | (0.0294) | (0.0294) | (0.0270) | (0.0251) | (0.0180) | (0.0292) | (0.0293) | (0.0642) | (0.0339) |
| Top 1% | | | 0.0103 | | | | | | | | | | |
| | | | (0.0431) | | | | | | | | | | |
| Top 10% | | | | 0.533*** | | | | | | | | | |
| | | | | (0.0271) | | | | | | | | | |
| Hindex | | | | | -0.0275*** | 0.0501*** | 0.0276*** | 0.0632*** | 0.0370*** | 0.0489*** | 0.0492*** | 0.0769*** | 0.0458*** |
| | | | | | (0.00462) | (0.0109) | (0.00914) | (0.00670) | (0.00599) | (0.0109) | (0.0109) | (0.0211) | (0.0123) |

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Hindex Squared | | | | | | -0.00412*** | -0.00406*** | -0.00496*** | -0.00140*** | -0.00408*** | -0.00409*** | -0.00374** | -0.00389*** |
| | | | | | | (0.000717) | (0.000577) | (0.000410) | (0.000331) | (0.000716) | (0.000716) | (0.00178) | (0.000836) |
| Log Alpha | | | | | | | -0.576*** | -2.178*** | | | | | |
| | | | | | | | (0.0498) | (0.124) | | | | | |
| Constant | -1.147*** | -1.140*** | -1.142*** | -1.440*** | -1.116*** | -1.184*** | -1.195*** | -1.142*** | -0.568*** | -1.247*** | -1.282*** | -1.506*** | -1.211*** |
| | (0.0705) | (0.0698) | (0.0701) | (0.0695) | (0.0702) | (0.0692) | (0.0635) | (0.0693) | (0.0376) | (0.0848) | (0.0779) | (0.0754) | (0.0710) |
| Semielasticity in the United States | -0.658*** | -0.556*** | -0.556*** | -0.581*** | -0.536*** | -0.553*** | -0.538*** | -0.565*** | -0.531*** | -0.519*** | -0.535*** | -0.291*** | -0.455*** |
| | (0.0216) | (0.0293) | (0.0293) | (0.0272) | (0.0308) | (0.0294) | (0.0297) | (0.0323) | (0.0171) | (0.0353) | (0.0320) | (0.0531) | (0.0361) |
| Semielasticity in Japan | -0.286*** | -0.231*** | -0.231*** | -0.231*** | -0.218*** | -0.244*** | -0.259*** | -0.249*** | -0.202*** | -0.210*** | -0.171*** | -0.149*** | -0.213*** |
| | (0.0438) | (0.0470) | (0.0471) | (0.0463) | (0.0477) | (0.0453) | (0.0433) | (0.0499) | (0.0267) | (0.0614) | (0.0583) | (0.0500) | (0.0473) |
| DIS | -0.372*** | -0.325*** | -0.326*** | -0.350*** | -0.318*** | -0.309*** | -0.279*** | -0.316*** | -0.329*** | -0.309*** | -0.363*** | -0.143* | -0.242*** |
| | (0.0503) | (0.0566) | (0.0567) | (0.0549) | (0.0581) | (0.0553) | (0.0535) | (0.0600) | (0.0321) | (0.0707) | (0.0672) | (0.0749) | (0.0608) |
| Observations | 32,813 | 32,813 | 32,813 | 32,813 | 32,813 | 32,813 | 32,813 | 32,813 | 32,813 | 32,813 | 32,813 | 7,546 | 21,827 |
| Pseudo R2 | 0.199 | 0.204 | 0.204 | 0.213 | 0.206 | 0.211 | 0.135 | 0.119 | 0.236 | 0.210 | 0.210 | 0.237 | 0.186 |
| Log pseudolikelihood | -21076 | -20958 | -20958 | -20701 | -20894 | -20769 | -20343 | -20727 | -30739 | -20794 | -20786 | -4911 | -14024 |

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

**Table 11: Descriptive Statistics at the USPTO Organizational Level**

| | Variable | Obs | Mean | Std. dev. | Min | Max |
|---|---|---|---|---|---|---|
| 1 | No. of Basic Patent Primary | 5,724 | 0.644 | 2.228 | 0 | 51 |
| 2 | No. of Basic Patent Included | 5,724 | 1.324 | 3.998 | 0 | 92 |
| 3 | Country | 5,745 | 0.680 | 0.467 | 0 | 1 |
| 4 | Post Period 82 | 5,724 | 0.958 | 0.201 | 0 | 1 |
| 5 | Interaction 82 | 5,724 | 0.653 | 0.476 | 0 | 1 |
| 6 | Post Period 83 | 5,724 | 0.950 | 0.219 | 0 | 1 |
| 7 | Interaction 83 | 5,724 | 0.648 | 0.478 | 0 | 1 |
| 8 | Post Period 84 | 5,724 | 0.942 | 0.234 | 0 | 1 |
| 9 | Interaction 84 | 5,724 | 0.644 | 0.479 | 0 | 1 |
| 10 | New Entrant | 5,724 | 0.768 | 0.422 | 0 | 1 |
| 11 | University | 5,724 | 0.068 | 0.251 | 0 | 1 |
| 12 | Cumulative Number of Basic Patents | 5,745 | 5.193 | 19.028 | 0 | 312 |
| 13 | Latest Number of Laser Diode Patents | 5,724 | 0.631 | 0.864 | 0 | 4.575 |
| 14 | Unemployment | 5,745 | 5.123 | 1.711 | 1.1 | 9.708 |
| 15 | GDP per Capita Growth | 5,745 | 1.511 | 1.991 | -5.370 | 12.162 |

**Table 12: Correlation Matrix USPTO Organizational Level**

| | Variable | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | No. of Basic Patent Primary | | | | | | | | | | | | | | |
| 2 | No. of Basic Patent Included | 0.898 | | | | | | | | | | | | | |
| 3 | Country | -0.209 | -0.225 | | | | | | | | | | | | |
| 4 | Post Period 82 | 0.006 | 0.009 | 0.011 | | | | | | | | | | | |
| 5 | Interaction 82 | -0.203 | -0.217 | 0.940 | 0.288 | | | | | | | | | | |
| 6 | Post Period 83 | 0.007 | 0.010 | 0.015 | 0.909 | 0.266 | | | | | | | | | |
| 7 | Interaction 83 | -0.202 | -0.216 | 0.929 | 0.284 | 0.989 | 0.313 | | | | | | | | |
| 8 | Post Period 84 | 0.002 | 0.008 | 0.027 | 0.844 | 0.260 | 0.928 | 0.303 | | | | | | | |
| 9 | Interaction 84 | -0.202 | -0.215 | 0.921 | 0.282 | 0.980 | 0.310 | 0.992 | 0.334 | | | | | | |
| 10 | New Entrant | -0.255 | -0.272 | 0.127 | 0.382 | 0.230 | 0.420 | 0.249 | 0.433 | 0.257 | | | | | |
| 11 | University | -0.037 | -0.044 | 0.111 | 0.018 | 0.111 | 0.011 | 0.108 | 0.013 | 0.107 | -0.014 | | | | |
| 12 | Cumulative Number of Basic Patents | 0.557 | 0.577 | -0.225 | 0.039 | -0.210 | 0.041 | -0.207 | 0.042 | -0.206 | -0.361 | -0.037 | | | |
| 13 | Latest Number of Laser Diode Patents | 0.576 | 0.640 | -0.282 | 0.060 | -0.256 | 0.062 | -0.253 | 0.058 | -0.253 | -0.363 | -0.081 | 0.533 | | |
| 14 | Unemployment | -0.093 | -0.095 | 0.590 | 0.074 | 0.550 | 0.029 | 0.519 | 0.010 | 0.497 | 0.079 | 0.073 | -0.082 | -0.100 | |
| 15 | GDP per Capita Growth | -0.005 | 0.000 | 0.030 | -0.113 | 0.010 | -0.058 | 0.034 | -0.070 | 0.027 | -0.095 | -0.001 | -0.040 | -0.041 | -0.274 |

**Table 13: Estimation Results at the USPTO Organization Level**

| Variables | 1<br>Poisson<br>1984<br>Primary<br>Full | 2<br>Poisson<br>1984<br>Primary<br>Full | 3<br>NB2<br>1984<br>Primary<br>Full | 4<br>NB1<br>1984<br>Primary<br>Full | 5<br>Poisson<br>1984<br>Primary<br>Full | 6<br>Poisson<br>1982<br>Primary<br>Full | 7<br>Poisson<br>1983<br>Primary<br>Full | 8<br>Poisson<br>1984<br>Primary<br>Until 1993 | 9<br>Poisson<br>1984<br>Primary<br>Included<br>Until 2003 |
|---|---|---|---|---|---|---|---|---|---|
| Post Period | -0.602*** | -0.583*** | -0.659*** | -0.603*** | -0.511*** | -0.502*** | -0.475*** | -0.563*** | -0.545*** |
| | (0.116) | (0.126) | (0.120) | (0.133) | (0.0757) | (0.154) | (0.144) | (0.132) | (0.131) |
| Country | 0.405** | 0.393** | 0.330** | 0.368** | 0.270*** | 0.343* | 0.428** | -0.0710 | 0.328* |
| | (0.164) | (0.167) | (0.161) | (0.180) | (0.103) | (0.184) | (0.178) | (0.229) | (0.173) |
| Interaction | -0.459*** | -0.445*** | -0.261* | -0.411** | -0.337*** | -0.413** | -0.493*** | 0.0205 | -0.244 |
| | (0.154) | (0.153) | (0.151) | (0.174) | (0.0929) | (0.175) | (0.168) | (0.162) | (0.156) |
| University | 0.438*** | 0.435*** | 0.442*** | 0.482*** | 0.336*** | 0.420*** | 0.423*** | 0.582*** | 0.401*** |
| | (0.100) | (0.100) | (0.0993) | (0.103) | (0.0635) | (0.0997) | (0.0999) | (0.167) | (0.110) |
| Cumulative Number of Basic Patents | 0.00153** | 0.00145** | 0.00326*** | 0.00192*** | 0.000595 | 0.00130* | 0.00136* | 0.00678*** | 0.00415*** |
| | (0.000716) | (0.000710) | (0.000809) | (0.000423) | (0.000568) | (0.000701) | (0.000706) | (0.00186) | (0.00101) |
| Latest Number of Laser Diode Patents | 1.235*** | 1.230*** | 1.243*** | 1.153*** | 1.222*** | 1.214*** | 1.221*** | 1.226*** | 1.180*** |
| | (0.0366) | (0.0417) | (0.0292) | (0.0237) | (0.0230) | (0.0412) | (0.0415) | (0.0610) | (0.0525) |
| Unemployment | -0.0746*** | -0.0726*** | -0.0656*** | -0.0685*** | -0.0400*** | -0.0575** | -0.0653*** | 0.0213 | -0.0588** |
| | (0.0231) | (0.0238) | (0.0211) | (0.0185) | (0.0147) | (0.0243) | (0.0241) | (0.0365) | (0.0255) |
| GDP per Capita Growth | 0.0216 | 0.0208 | 0.0218* | 0.0217** | 0.0318*** | 0.0204 | 0.0228 | 0.0396** | 0.0367** |
| | (0.0150) | (0.0147) | (0.0132) | (0.0108) | (0.00892) | (0.0150) | (0.0149) | (0.0196) | (0.0173) |
| New entrant | | -0.0387 | -0.0782 | -0.128** | -0.0117 | -0.0884 | -0.0663 | -0.123 | -0.0187 |
| | | (0.0792) | (0.0632) | (0.0545) | (0.0497) | (0.0786) | (0.0790) | (0.137) | (0.0939) |
| Log Alpha | | | -0.628*** | -0.472*** | | | | | |
| | | | (0.102) | (0.0964) | | | | | |
| Constant | -1.297*** | -1.292*** | -1.340*** | -1.102*** | -0.752*** | -1.357*** | -1.385*** | -1.555*** | -1.314*** |
| | (0.124) | (0.125) | (0.122) | (0.135) | (0.0770) | (0.152) | (0.142) | (0.152) | (0.134) |
| Semielasticity in the United States | -0.654*** | -0.642*** | -0.602*** | -0.637*** | -0.572*** | -0.600*** | -0.620*** | -0.419*** | -0.546*** |
| | (0.0314) | (0.0399) | (0.0416) | (0.0431) | (0.0292) | (0.0463) | (0.0438) | (0.0702) | (0.0519) |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Semielasticity in Japan | -0.452*** | -0.442*** | -0.483*** | -0.453*** | -0.400*** | -0.395*** | -0.378*** | -0.430*** | -0.420*** |
| | (0.0634) | (0.0702) | (0.0620) | (0.0730) | (0.0454) | (0.0931) | (0.0893) | (0.0751) | (0.0759) |
| DIS | -0.202*** | -0.200*** | -0.119* | -0.184** | -0.172*** | -0.205** | -0.242*** | 0.0118 | -0.125 |
| | (0.0733) | (0.0745) | (0.0711) | (0.0827) | (0.0496) | (0.0963) | (0.0924) | (0.0934) | (0.0830) |
| Observations | 5,724 | 5,724 | 5,724 | 5,724 | 5,724 | 5,724 | 5,724 | 1,456 | 3,794 |
| Pseudo R2 | 0.514 | 0.514 | 0.239 | 0.221 | 0.588 | 0.512 | 0.513 | 0.439 | 0.491 |
| Log pseudolikelihood | -4348 | -4348 | -4120 | -4217 | -6244 | -4368 | -4361 | -1217 | -3002 |

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

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