Three Essays on Human Capital Factors and Firm Innovation

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Abstract

This dissertation examines how the management of human capital factors impacts firm innovation. The first chapter produces causal estimates of the asset value of inventors to firms following inventors' unexpected deaths. The second chapter studies how multinational entities manage patent innovation in context of reforms to migration policy that shift the ease of business-related travel. The third chapter explores how the breadth and depth of expert reviewers' knowledge impacts their preferences for financing novel innovation in individual R&D review settings through examining the case of scientific grant review.

Contents

Dedication

To Julianne Corbin, my wife and forever partner, without whom none of this would have been possible had she not been in the foxhole with me. And to my family, who supported me throughout.

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Chapter 0

Introduction

Among economists and management scholars, innovations are theorized to emerge from the recombination of technological components and ideas, and such recombination is thought fundamental to economic growth. Romer (1990) presents a model in which economic growth is endogenous to the production of new knowledge, with knowledge outputs entering input stocks and consequently impacting the ease of new knowledge creation. Due to its recombinatoric elements, the model can explain observed phenomena in economic growth previously only explained via exogenous factors (Solow, 1956). Likewise, Weitzman (1998, p. 331) notes that "[a]s has been generally recognized for some time now, the long-term growth of an advanced economy is dominated by the behavior of technological progress." To demonstrate, the author constructs a model of economic growth driven by recombinatoric production and delineates its principles, finding that output emerges from an infinite recombinatoric technological production space and "that the ultimate limits to growth lie not so much in our ability to generate new ideas as in our ability to process an abundance of potentially new ideas into usable form" (Weitzman, 1998, p. 331).

However, the potentially infinite landscape of technological solutions requires a dependence on knowledge brokering and human capital for firms to succeed, specifically, and for the economy to grow, generally. Hargadon and Sutton (1997) study product innovation at an ideation consulting and design firm and find that recombination emerges via knowledge brokering. In their case study, the firm examined acted as a broker that sources and transfers knowledge of technological solutions across industries and firms, and in doing so it achieved novel innovations from recombining technology-related knowledge. In Romer (1990), human capital investments for knowledge production are highlighted as core to achieving sustained growth. On a more micro level, theory (Rosenberg, 1996) and empirical evidence (Fleming, 2001; Fleming and Sorenson, 2004) focused on innovation processes posit that innovation-induced uncertainty leads to fundamental uncertainty in the value of new technological goods, and that this uncertainty induces costs, frictions and inefficiencies on economic transacting around innovations (Rosenberg, 2010; Nelson, 1959). Consequently, familiarity with technology (Fleming, 2001) and investment in scientific knowledge (Fleming and Sorenson, 2004; Nelson, 1959) are demonstrated to facilitate successful navigation of the innovation landscape.

The difficulty this engenders for firms is that the high-skilled human capital necessary for managing knowledge and innovation is scarce. While innovation and the production of new technologies requires investment in knowledge accumulation in order to reach the novelty frontier and to produce new technological and knowledge goods (Jones, 2009; Boudreau et al., 2016), no one individual can feasibly know or access today the stock of all knowledge. Humans are fundamentally limited in their learning by age and information processing constraints, and these limits lead to increasingly longer time investment in learning prior to innovating, increasingly narrow specialization on the part of innovators, and increasingly greater reliance on teamwork in order to produce technology goods (Jones and Weinberg, 2011; Jones, 2009; Wuchty et al., 2007).

Firms must therefore strategically manage their knowledge resources in order to succeed in the modern economy. The knowledge-based view of the firm (Kogut and Zander, 1992, 1996) posits that firms' competitive advantages and their performance outcomes depend on their capabilities at managing the flow and recombination of knowledge, and consequently human capital, particularly for innovation purposes. However, studies identifying the causal effects of access to human capital and human resource management practices on firms' innovation are few.

The purpose of this dissertation is to study how management of human capital-related factors causally impacts firms' innovation outcomes. Specifically, I empirically investigate how three broad factors, (1) access to diverse human capital, (2) human capital public policies, and (3) innovation evaluation and funding management processes, influence the rate and direction of firm innovations and, in turn, produce implications for firm strategy.

In the first chapter, "The Value of Innovators to Firms: Causal Evidence on Inventor Death and Firm-Level Response", I link the availability of innovative talent to firms' market valuations. After connecting inventors on all USPTO patents from 1976 – 2018 to firms indexed in data from the Center for Research in Security Prices (CRSP), I estimate the average value of the inventor to the firm as well as value conditional on certain industries and human capital skill types. I do so by leveraging unexpected inventor deaths as a source of exogenous variation in firms' human capital assets. Using event study methods, I estimate that the average inventor's human capital is worth approximately 27% of the value of a granted patent and exhibits asset value of between $400 thousand and $1.4 million USD, depending on sample and adjustments. Investigation of short-run market response in a 15-day window following inventor losses demonstrates that equity losses persist, suggesting the market anticipates longer-run costs of inventor death. Additional results explore how value varies as a function of inventor heterogeneity according to industry and four human capital types suggested by the literature to be of-value: creativity, superstar status, reliance on science, and team experience. While these results are not able to sort whether heterogeneous effects are driven by causal relationships or selection (e.g. can training an inventor to be creative produce more value?), they do produce evidence for the value of human capital-related recruitment and training strategies for firms.

The second chapter, "Migration Policy Reform and Global Collaborative Patenting within Multinational Firms: Causal Multi-country Evidence" (from joint work with Dany Bahar and Prithwiraj Choudhury), explores how reforms that positively encourage permanent business-related migration impact multinational entities' (MNEs) management and production of globalized innovations within the reforming countries. Specifically, it examines the production of global collaborative patents, those patents which involve international co-inventor teams. Through leveraging an event study framework, we produce estimates of how 14 pro-business related migration reforms impact patent production by over 360,000 MNE subsidiaries within the reforming countries controlled by over 9,000 MNEs during the years 2000 - 2013. We demonstrate three key results. First, we find that pro-business immigration reforms lead to greater production of patents overall and global collaborative patents specifically by impacted MNE subsidiaries. An enacted reform encouraging migration is associated with a 2.1% average marginal increase (or an additional 0.014 patents) in MNE subsidiary production of global collaborative patents among all a subsidiary's inventors. At the same time, reforms engender an almost 1% increase in annual global collaborative patent production among migratory subsidiary inventors. Second, we show that these effects are driven primarily by larger multinational entities, who exhibit percent increases approximately four times that of smaller MNEs. Finally, we show that the impacts of reforms are not confined solely to immigrants, as most of the increase in GCPs produced after reform enactment occurs primarily among non-immigrated inventors. This suggests that the reforms produce a substantial 'spillover' effect through encouraging knowledge flows and novel recombination. Taken together, these results provide novel, multi-country and multi-event support for the core theory of the knowledge-based view of MNEs, namely that the MNE's foundation rests on a comparative advantage in moving human capital across international borders (Caves, 1971). From a strategy perspective, the results hold implications for governmental policymakers, suggesting that different reform types are conducive toward promoting countries' innovation capabilities, and for firm managers, who allocate innovation resources with respect to international human capital policies.

In the third chapter, "Who Should I Trust in the Face of the Unknown? Depth, Breadth, and the Evaluation of Novel Ideas", I leverage experimental data on scientific grant review and evaluators' prior scientific publications from Boudreau et al. (2016) to investigate how heterogeneity in expert evaluators' science-based knowledge and experience influences their preference for novel innovations generally, as well as their tastes for novelty specifically when that novelty varies across the innovations they observe. As prior research suggests that evaluators with greater proposal-relevant expertise prefer innovations with intermediate levels of novelty and are biased against highly-novel projects (Boudreau et al., 2016; Criscuolo et al., 2016), but that breadth of expertise may facilitate accurate evaluation in context of novel ideas (Criscuolo et al., 2016; Gentner, 1983; Hong and Page, 2009), I investigate in the experimental data how the structure of knowledge-based expertise, defined by the dimensions of breadth, depth, and relatedness, associates with evaluators' preferences for the early-stage grant proposals they review. I find, first, that related-breadth and related-depth are associated with more critical review of proposals, but that breadth of expertise correlates positively with proposal evaluations when proposals exhibit greater novelty to the evaluator. The magnitude of this effect is large enough that a single standard deviation increase in the breadth of knowledge domains an evaluator is familiarized with can lead to a negation of bias against proposals in the highest third of novelty. Second, I show that prior investment in unrelated expertise is significantly associated with a substantially greater preference for innovations (with a standard deviation increase in the depth of an evaluator's unrelated knowledge associated with as much as a three point increase in perceived innovation impact on a 10 point scale), even when controlling for evaluators' breadth and depth of related-knowledge. Further, when considering the proposals in the highest third of novelty, measures of investment in unrelated knowledge are shown to correlate positively with perceived innovation impact. These results line up well with prior evidence and theory which suggests that knowledge outside of the problem domain and marginality of perspective are valuable for identifying extreme high-performance solutions (Gentner, 1983; Jeppesen and Lakhani, 2010). Overall, as I find that breadth of expertise is associated with greater preference for highly-novel innovations, even when holding depth of expertise fixed, the results suggest that novelty biases may be overcome through design of evaluation processes, specifically through selection of certain types of evaluators with broad knowledge, without losing the benefits of depth of expertise (namely, critical review). These results hold substantial strategy implications for managers of human capital engaged in R&D and innovation processes, who may wish to pursue varying levels of novelty in line with organizational R&D portfolio goals.

Chapter 1

The Value of Innovators to Firms: Causal Evidence on Inventor Death and Firm-Level Response

> A man may die, nations may rise and fall,
> but an idea lives on.
>
> John F. Kennedy

1.1 Introduction

What is the value of the innovator to the firm? Which types of innovative human capital are of more or less value?[1] To what extent does heterogeneity in value depend on industry? These questions are difficult to answer due to the fundamental uncertainty characteristic of valuing innovations, which only resolves over time as outputs are realized.[2] Valuing innovator human capital is further complicated as the quality of

[1]Economics and management scholars have conceptualized human capital as the cumulative knowledge, skills, training, and experiences of individuals (Becker, 1962; Mincer, 1958; Schultz, 1961).

[2]The outputs of innovation (i.e. ideas and inventions) are inherently novel, and this novelty generates fundamental value uncertainty that resolves only after invention and application (Rosenberg, 1996; Fleming, 2001). As a result, estimates of the value of innovators' work largely rely on realization of long-run impacts. For instance, estimating the value of patented inventions for the econometrician generally relies on either measurement of realized citations

its outputs - ideas and discoveries - depends on complex processes involving technological and knowledge interdependence (Jones, 2009; Murmann and Frenken, 2006; Simon, 1997), diversity of knowledge inputs (Østergaard et al., 2011; Burt, 2004), and specialization and team production (Wuchty et al., 2007; Faraj and Sproull, 2000; Becker and Murphy, 1992).[3] Yet, estimating its value is core to firm strategy. The knowledge-based view of the firm suggests that competitive advantages emerge from developing knowledge and technology-related capabilities via the firm's talent pool, and that the critical question managers face is how to "organize individuals to generate knowledge that the firm seeks" (Nickerson and Zenger, 2004, p. 618).[4] Corresponding to this perspective, firm managers often estimate potential human capital 'value-add' to make decisions related to talent management (e.g. hiring, promotion, and firing), resource allocation (e.g. staffing, allocation of financial and physical capital), and the organization of research, development, and commercialization, while leaders of knowledge-intensive firms often cite poor talent-related decision making as their largest cost.[5]

In the present study, I use the unexpected deaths of inventors in a premature-death design to produce causal estimates of the value of innovator human capital to the firm over the short-run. These causal estimates then serve as the basis from which to evaluate the knowledge-based view of the firm and its importance for managerial strategy and heterogeneity in managerial practice. Short-run estimates of inventor asset value

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indicating scientific value (e.g. Hall et al. 2005) or on realized stock market returns (e.g. Pakes 2018; Austin 1993; Nicholas 2008; Kogan et al. 2017) while managers often must form and navigate 'blue ocean' markets, educating consumers about the value of inventions, to achieve market return. Short-run indicators may also provide faulty estimates of innovation value. For example, Wang et al. (2017) demonstrated that short-run citation-based indicators in science are biased against highly novel discoveries. This short-run measurement uncertainty limits the scope over which firms can contract for innovations (Manso, 2011; Holmstrom, 1979; Arrow, 1962)

[3]Adding human capital to an innovator talent pool may yield novel knowledge inputs (Burt, 2004; Hargadon and Sutton, 1997; Fleming, 2001) or useful positive peer effects that aid in discovery, such as those spillovers originating with superstars (Azoulay et al., 2010), or from helpful peers (Oettl, 2012), mentors (Waldinger, 2016), marginal perspectives (Jeppesen and Lakhani, 2010), and scientific knowledge (Fleming and Sorenson, 2004). Simultaneously, adding human capital to a talent pool can introduce costs due to teamwork difficulties, such as moral hazard and monitoring, (Holmstrom, 1982), team process formation, (Tuckman, 1965), and communication of tacit knowledge (Aral and Van Alstyne, 2011; Cowan et al., 2000).

[4]For additional overview of the Knowledge-Based View, see Kogut and Zander (1992, 1996); Conner (1991); Demsetz (1988); Nickerson and Zenger (2004); Conner and Prahalad (1996); Grant (1996), among others.

[5]The costs of failure to evaluate talent can be significant. According to the U.S. Department of Labor, a bad hire can cost approximately 30% of the employees' annual wages; according to further surveys, replacement costs for such hires can range between $7,000 to $40,000 (Cardenas, 2014). Thus, significant costs can emerge due to errors in estimating fit among high-skilled human capital. Given the frequently high salary of innovating employees (e.g. one estimate puts inventors' annual average earnings at approximately $144 thousand, see Jaravel et al. 2018), recruitment mismatch of innovators and other inaccurate strategy decisions surrounding innovative talent and estimates of innovator value can pose substantial costs to firms. For instance, the CEO of Zappos, a popular e-commerce firm, stated that bad hires had cost his company in excess of $100 million (Falon, 2016).

suggest that inventors are valuable to the firm (on average worth between $400 thousand and $1.2 million in 2012 USD), that certain inventor types exhibit greater or lesser value (superstars are estimated to be roughly 3 times as valuable as the mean inventor, for example), and that inventor asset value varies across industries (inventors appear to convey to firms relatively little value in the transportation equipment industry, for example).

To produce these estimates, the study proceeds as follows. Section 1.2 discusses the identification strategy and associated data. Of almost 7 million patents granted from 1976-2018 by the United States Patent and Trademark Office (USPTO), I match just over 2 million patents and 1.3 million unique inventors to financial performance data for almost 10 thousand firms indexed in the Center for Research in Security Prices (CRSP) database. Within the firm-matched data, I identify 3,095 'prematurely deceased' inventors from parsing of patent bibliographic text, 686 of who produced firm-matched utility patents before their premature deaths and meet other criteria to ensure their deaths are exogenous news. These inventors serve as the sample for the main analysis.

In Section 1.3, I leverage this data to assess the stock market's short-run asset valuation of innovator human capital. In financial event-studies, I estimate the difference in mean asset value assigned by the market to patents which announce inventor deaths as compared with those that do not among the subset of inventors with patents of both types matched to the CRSP data. I find that the mean human capital of a deceased inventor is worth roughly $1.2 million USD in 2012 dollars, on average, among the sample of inventors examined in the study and that the asset value of human capital exhibits a long tail. This estimate is shown to be robust to controlling for the inventor, the timing of their death, the firm at which they are likely employed in advance of their death, and the primary technology class in which the inventor works. While the sample of inventors examined in analyses is characterized by positive selection on superstars and creative inventors who produce patents of substantially greater patent value than the population of all inventors, a back-of-the-envelope calculation would still suggest that the asset value of the average inventor in the population is likely roughly $310,000 USD.[6]

Section 1.4 then focuses on additional analyses. The first analysis examines whether inventor asset value varies as a function of industry and human capital type. The results show that superstar inventors,

[6]This estimate is achieved by weighting the asset value estimate of the sample according to the relative patent values between the sample and the total population of alive inventors from Table 1.1.

creative inventors, and inventors who rely on science are estimated to have asset values more than twice that of the average inventor (although these estimates are only significant for superstar inventors), whereas inventors with substantial team experience are estimated to have significantly positive but below-average asset values. Additionally, results also demonstrate that inventor asset value varies by industry. At the SIC2 Major Group level, inventors are found to have positive asset value in major groups related to chemicals and electronics but exhibit relatively little asset value in oil & gas extraction and in transportation equipment industries, for example.

The second analysis in this section then examines the implications for firms' market performance following signals of deceased inventors. In further patent grant-based event studies, I find that firms associated with inventor death news face a substantial and lasting (at least 15-day) decrease in asset value due to negative cumulative abnormal returns between 0.16% and 0.31%, suggesting market anticipation of reduced performance and that, in the short-run, lost human capital asset value is difficult to replace.[7]

Section 1.5 discusses the implications of these results, their limitations, and the study contributions, of which there are two main contributions. First, I report novel causal estimates of the asset value of innovative human capital. In doing so, I contribute to previous literature that estimates the market value of innovations, but not of human capital per se, via analyses of firm financial returns (Kogan et al., 2017; Austin, 1993; Pakes, 2018; Hall et al., 2005; Nicholas, 2008). This study is the first (to the author's knowledge) to directly estimate an asset value for innovative human capital and introduces a novel approach to do so. Second, the results contribute causal evidence in support of the knowledge-based view of the firm and associated theory. Particularly, the results show a positive asset value of inventors independent of intellectual property and labor contracts, and additionally indicates that heterogeneous human capital types are of varying context-dependent importance for firms' competitive advantage.

Overall, the findings suggest that inventors are a complementary asset to firms, and that firms face significant costs to inventor losses that impose hurdles which firms may struggle to overcome. The study

[7] Although seemingly small, these returns represent substantial losses when considered at the level of firm market value. Additionally, these abnormal returns are similar to prior estimates in the literature. Kogan et al. (2017), while examining the large sample representing all patent grants from 1926 - 2010, finds mean abnormal stock returns surrounding patent grant events of only 0.07% while Austin (1993) analyzes market returns attributable to 565 patent grants awarded to 20 large biotech firms and finds that the grants induce positive abnormal stock returns of between 0.27% and 1.91%, depending on which subset of patents is analyzed, with the majority of patents at the low end of that range.

shows evidence that the values of firm-affiliated patent grants are suppressed following an inventor's death, even when the news of the inventor's death is no longer novel, suggesting that inventors and their human capital may well be complementary assets important to exploiting the value of intellectual property. Additionally, the evidence of firms' inability to quickly recover lost asset value subsequent to inventor losses highlights that human capital is a hard-to-replace asset, at least in the short-run. Therefore, firms may be well served by creating resilient innovator talent pools, either through ensuring redundancy in expertise and valuable human capital types or through constructing a resilient innovation talent pool via recruitment and training. However, such investments are clearly context and industry dependent - even when invention is prolific within an industry, inventor human capital may not be key to firm performance.

1.2 Empirical Identification: Exogenous Inventor Deaths

The empirical setting for this study is inventors of United States Patent and Trademark Office (USPTO) patents and their employers (the associated publicly listed firms to which the patents are assigned). In order to produce causal estimates of the value of firms' access to inventors' human capital, it is necessary to identify *exogenous variation* in firms' talent pools. To do so, I measure the unexpected deaths of inventors in a premature death-design study, wherein firms unexpectedly face inventor losses. By mining USPTO patent bibliographic data, I measure 3,095 premature inventor deaths that impact public firms at the point of death, 686 of which remain after adjusting for exogeneity and other corrections. In this section, I discuss the death-design identification approach, measurement of these inventor deaths, and steps taken to ensure the measured deaths capture exogenous variation.

1.2.1 Unexpected Inventor Deaths as a Shock to Firm's Human Capital Pools

To understand why a death design study is necessary, consider a study based on inventor movements. In such a study, estimating the value of innovators to firms is difficult due to endogenous labor market matching. Innovators join and leave companies based on wage signals, technical alignment, and learned fit, in addition to other idiosyncratic factors, and firms hire and fire based on inferences regarding inventors' likely contributions that are unobserved by the econometrician. As a result, simply estimating the consequences of changes in employment is likely to understate inventors' value as, absent exogenous frictions, markets and firms likely anticipate and adjust for changes in employment. Any valuations of inventors derived from such movements are therefore likely 'priced-in' and estimates biased toward zero.

Consequently, valuation of innovative human capital requires *exogenous variation* in firms' access to talent. To produce causal estimates, I leverage a natural experiment that produces such variation: the unexpected deaths of inventors. Premature, unexpected inventor deaths generate a short-run quasi-experiment on treated firms in which the market receives unanticipated and exogenous news that an inventor is deceased and adjusts its valuation of the firm based on this news. From this adjusted valuation, it is possible to infer the market value assigned to the lost human capital.

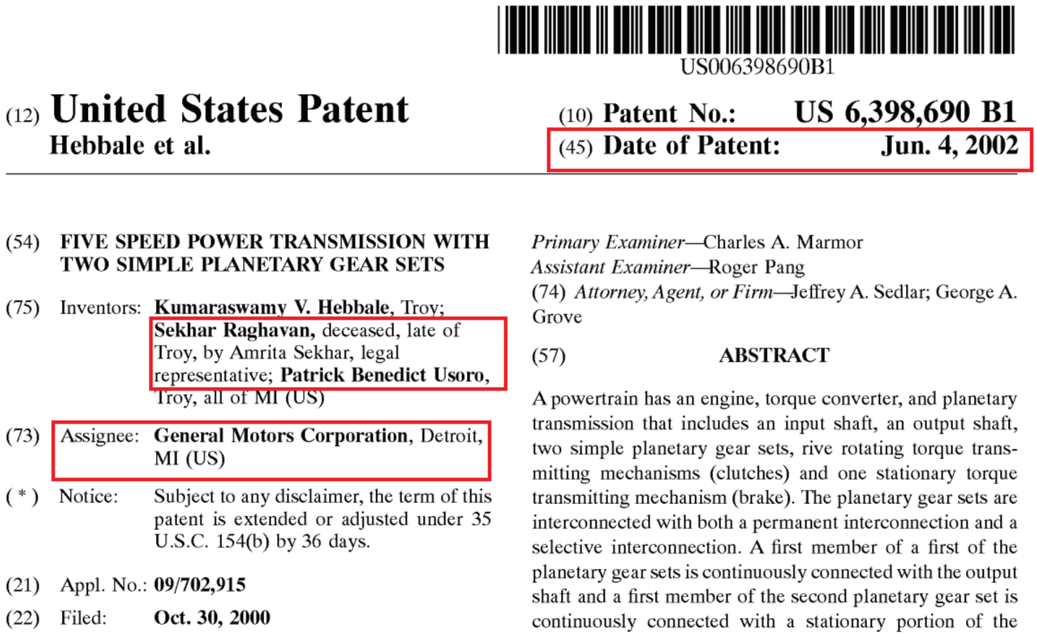
Measuring Deceased Inventor Announcements in Patent Records

Following previous patent death-design studies (e.g. Hong 2019; Jaravel et al. 2018), I identify inventor death events from patent grant and application records. Specifically, I measure 7,309 'unexpected' inventor deaths (defined by an inferred career age of 30 years or fewer) from the bibliographic information of all USPTO patents granted between 1976-2018 (over 6.8 million patents) as well as patent applications published publicly between 2001 and 2018 (over 8 million patent applications). These deaths are measured via customized text parsing of both the patent bibliographic data as well as fields indexed in publicly available patent metadata datasets.[8]

Examples are instructive for understanding how inventor deaths are identified and measured. Consider Sekhar Raghavan, an inventor granted patents during the period of Dec. 11, 1997 - Jun. 4, 2002. On June 4th, 1997, Sekhar Raghavan and Kumaraswamy V. Hebbale apply for the U.S. Patent No. 5836850A, entitled 'Four Speed Power Transmission', which is granted on December 11^{th}, 1997 with intellectual property rights assigned to General Motors Corporation of Detroit, Michigan. Following this grant, Mr. Raghavan applied for and received patent grants for 14 inventions, all related to automotive transmissions and all of which are assigned to General Motors Corporation.

However, for Mr. Raghavan the bell tolls at or prior to June of 2002, only five years after his first patent application. Figure 1.1 displays the bibliographic data for Patent No. US-6,398,690-B1, granted and assigned to General Motors Corporation on June 4^{th}, 2002. As can be seen, the patent record is useful for

[8] I parse search results from Google's Patent Search as well as fields in USPTO's PatentsView database. Parsing is described further in Appendix A.1



US006398690B1

(12) **United States Patent**
Hebbale et al.

(10) **Patent No.: US 6,398,690 B1**
(45) **Date of Patent: Jun. 4, 2002**

(54) **FIVE SPEED POWER TRANSMISSION WITH TWO SIMPLE PLANETARY GEAR SETS**

(75) Inventors: **Kumaraswamy V. Hebbale**, Troy; **Sekhar Raghavan,** deceased, late of Troy, by Amrita Sekhar, legal representative; **Patrick Benedict Usoro**, Troy, all of MI (US)

(73) Assignee: **General Motors Corporation**, Detroit, MI (US)

(*) Notice: Subject to any disclaimer, the term of this patent is extended or adjusted under 35 U.S.C. 154(b) by 36 days.

(21) Appl. No.: **09/702,915**

(22) Filed: **Oct. 30, 2000**

Primary Examiner—Charles A. Marmor
Assistant Examiner—Roger Pang
(74) *Attorney, Agent, or Firm*—Jeffrey A. Sedlar; George A. Grove

(57) **ABSTRACT**

A powertrain has an engine, torque converter, and planetary transmission that includes an input shaft, an output shaft, two simple planetary gear sets, rive rotating torque transmitting mechanisms (clutches) and one stationary torque transmitting mechanism (brake). The planetary gear sets are interconnected with both a permanent interconnection and a selective interconnection. A first member of a first of the planetary gear sets is continuously connected with the output shaft and a first member of the second planetary gear set is continuously connected with a stationary portion of the

Figure 1.1: An Example Patent Grant Announcing an Inventor's Death

Notes: The figure presents the top half of the first page of bibliographic information for United States Patent 6,398,690B1 which announces the death of Sekhar Raghavan. The patent displays key information regarding inventors involved with the patent and their living status, regarding the entities to which intellectual property rights are assigned (usually firms or organizations), and key information regarding the technical and timing aspects (e.g. grant and application date) of the awarded intellectual property rights and corresponding invention.

determining key information regarding the inventors and the firms from which the invention emerges as well as invention timing. In addition to technical information, the patent records the date of grant, the date of application, inventor and limited geolocation information, and the firm or other assignee to which intellectual property rights are granted.

The patent record also discloses the living status of the inventors, and, consequently, notice of Mr. Raghavan's death. As he is listed on the patent as deceased and his inventorship rights are granted to his legal representative and likely relative, Amrita Sekhar, it can be determined that Mr. Sekhar contributed to at least one of the protected intellectual property claims for which the patent was granted (he is listed as an inventor), but that he passed away prior to the patent publication (he is listed as deceased).

Through examining the corpus of USPTO patent records in the same manner, I am able to construct a reliable measure of patent deaths.[9] Parsing of the patent corpus identifies 11,530 such notices of inventor

[9]The USPTO patent application process requires that all inventors who contributed to any of a patent's covered intellectual property claims, both living and deceased, are recorded on applications or eventual grants, and provides substantial legal incentives for patent assignees (typically, firms) and inventors to correctly list inventorship at the risk of potential patent invalidation. As a result, patent records often contain notices that inventors are 'deceased'.

death, corresponding to 7,516 inventors identified as eventually deceased.

After collection of deceased inventor records, I harmonized and matched the deceased inventors to the USPTO PatentsView data files, which allow for disambiguated matching of granted patents to (i) the inventors with which they are associated and (ii) the firms to which they are assigned. PatentsView usefully indexes key information on all patent grants published from 1976 to 2018, totaling just over 6.8 million patents matched to about 3.7 million unique inventors and just over 682 thousand unique patent assignees. For additional details on the legal incentives faced by firms and inventors to ensure complete and correct inventorship listings on patent records as well as for discussion of nuances in the construction of the sample of deceased inventors and how those inventors are matched to the USPTO PatentsView dataset, see Appendix A.1.

1.2.2 Exogeneity of Inventor Death Announcements and Sample Determination

For analyses, identification requires the assumption that the measured inventor death announcements index exogenous news to the market - that is, the market learns and responds to novel information about the loss of an inventor at the point of patent grant and publication. To support this assumption, I limit the data by assessing the value assigned to inventors of utility patents (1) who likely died unexpectedly (as identified by an observed career age of 30 years or less), (2) whose death announcements were not preempted by prior publicly-published patent applications, and (3) who have firm-matched patents prior to the patent announcing their death. Doing so reduces the sample for the initial analysis to a primary consideration set of 686 inventors with 7,693 patents of which 1,347 patents signal an inventor death.

Two steps are taken to ensure that the inventor death announcements measured are 'unanticipated' by the market. First, following standard practice in death-design studies, I focus only on inventors who are deceased at an early age. As I am unable to directly observe actual ages of inventors, I infer a career age for each inventor based on the dates of their first and last patent applications as well as their dates of

These notices were systematically recorded and reported by the USPTO through at least 2012 and exhibit substantial consistency in reporting over time. As of December 4th, 2012, the patent office removed from its raw XML files the field used to track deceased inventors and has not yet established a new system for tracking deceased inventors in raw patent publication data (confirmed via email with USPTO on Aug. 30, 2019). This has resulted in reduced reporting of deceased inventors. See Appendix A.1 for additional discussion of the frequency of 'deceased' announcements identified.

death inferred from patent bibliographic documents. I limit this career age to be no more than 30.[10] Doing so selects for unexpected deaths corresponding to individuals deceased suddenly and at an early age. For robustness checks, I additionally consider the sample of inventors deceased at only 15 years of career age or less.

Second, in order to ensure novelty of the deceased inventor news to the market, I further constrain the sample to those patent grants where the signaled death was not 'preempted' by a separate published announcement (e.g. in a published application for the patent or in another patent grant), and where patent-firm linkages exist prior to an inventor's death.[11]

Beyond restricting the grants analyzed, I performed qualitative checks to assess whether 'deceased' notices on patents are novel information processed by the market at the point of announcement and generally not preempted by outside news sources, including interviewing a former finance trader and market analyst who specialized in bio-pharmaceutical and scientific markets. The interview suggests that common practice for at least some finance market participants is to pay attention to patents and patent's inventor-related information, often using standardized third-party Bloomberg Terminal news aggregation services that facilitate tracking and inspection of patents granted to firms. At the same time, but for the case of superstar inventors tracked idiosyncratically by specialist analysts, the interviewee indicated that it is largely unheard of to track inventor deaths or firm talent pools via other sources (e.g. obituaries), and the interviewee was unfamiliar with any tools for that purpose.

Despite this anecdotal evidence, one concern may be that market analysts learn from news or obituary announcements that inventors are deceased in advance of the patent grant and that they connect this information to firm performance. To further confirm that digital obituaries were unlikely to preempt the death notice information, I conducted an obituary search for a randomly sampled set of 70 of the deceased inventors that included 19 superstars and 24 inventors with inferred dates of death in the year 2000 or later.

[10] The 30-year career age limit is in-line with standard practice in similar studies of premature inventor deaths. Hong (2019) applies the same standard, whereas Jaravel et al. (2018) measures premature deaths based on an actual age of 60 years or less. Even accounting for advance degree attainment this is in-line with an assumed 30-year career age (PhDs are awarded on average to individuals' in their early 30s, for example).

[11] The results presented prove robust to whether all deceased notices are analyzed (e.g. all 1,303 signals) or if only the first such notice (e.g. 683 signals) is analyzed. This suggests either that the market may exhibit some inefficiencies with respect to notices of inventor deaths, and that it may 'learn' of the death each time a notice is published, or, alternatively, that inventors are complementary assets to patent grants, and that their absence weakens the value of related intellectual property rights.

For this set, notable news was found for only 3 inventors. The search is discussed in detail in Appendix A.1.6, but the results of the search overall reinforce the idea that financial market participants would have been unlikely to find news of inventor deaths outside of patent grants.

1.2.3 Matching to Center for Research in Security Prices (CRSP) Data

To examine the return of inventor human capital to firm asset values, I match the patent and inventor data to paired permanent security identification numbers (permnos) and permanent company identification numbers (permcos) from the Center for Research in Security Prices (CRSP) database. I do so through harmonizing a final set of matches between patents and CRSP identifiers based on the three data sets connecting patents to firms. The first two are existing matched links between firm-level identifiers and patents (drawn from Kogan et al. 2017 and Autor et al. 2016), while the third source is a match I construct of patents to firm identifiers in both CRSP and Compustat. For further detail on the matching process, see Appendix A.2. In this process, I match just over 2.3 million patents and their applications to just over nine thousand firm securities.

1.2.4 Final Sample of Deceased Inventors

As a result of the matching and adjustments, as well as additional adjustments for measurement error in the patent data (see Appendix A.1.4 for a breakdown of how the sample of inventors and deceased inventor notices changes conditional on restrictions), I focus on a remaining subset of 3,095 unexpectedly deceased inventors and match them to firm records. In the analyses that consider only the first announcement of an inventor's death and compare the valuation of inventor patents before and after death, I focus on 686 inventors with 7,693 patents. Of these patents, 7,601 are utility patents and 1,303 of those patents signal that an inventor is deceased without signaling as such on any published patent application (683 of which are the first such announcement). In later analyses looking at the impact of just-deceased inventor patent grants on firm financial security performance surrounding the patent grant, I broaden these restrictions and focus on up to 3,644 patent records announcing an inventor's death.

Table 1.1 provides summary statistics on the deceased inventors identified as well as the full population of inventors with no such notices. Relative to the average inventor never identified as deceased, the deceased

Table 1.1: Inventor Summary Statistics

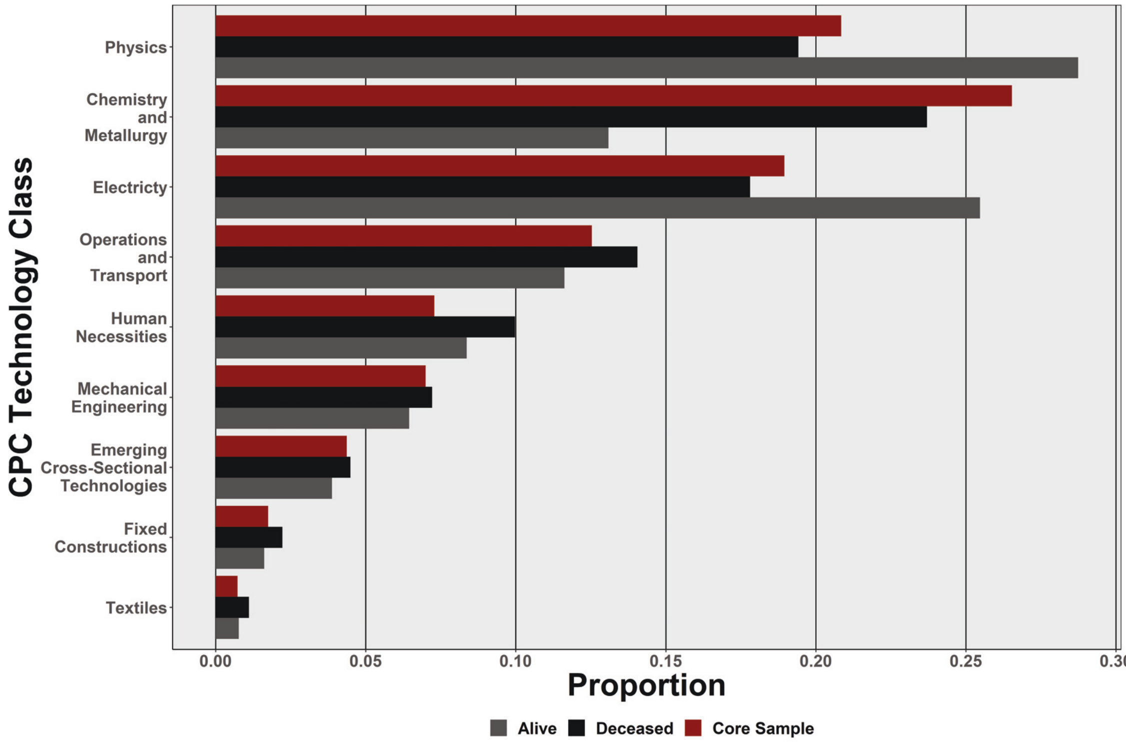
	Alive N = 1,305,600				Deceased 30 N = 2,447		Core Sample N = 686	
	Mean	SD	Min	Max	Mean	SD	Mean	SD
Career Age	7.51	8.54	1	103	10.14	7.94	12.71	7.14
Num. Patents	7.10	17.86	1	5,442	8.89	14.69	11.12	14.37
Num. Patents/Year	1.02	0.89	0.02	176.33	0.87	1.15	0.93	1.34
Mean Citations	5.58	12.64	0	931	8.01	12.98	9.81	14.21
Mean Tech-Weighted Citations, 5 yr.	0.23	0.45	0	56.84	0.34	0.43	0.41	0.38
Mean Team Size	3.78	2.22	1	65	3.42	1.98	3.02	1.45
Mean Days to Patent	1,045.72	500.21	9	23,921	905.61	459.40	813.68	268.89
Mean Patent Value/Inv.	722,677.70	8,031,736.00	0.06	503,315,346.00	1,699,772.00	22,693,683.00	2,776,628.00	32,882,805.00
Num. Deceased Patents	0.01	0.16	0	31	1.51	1.75	1.98	2.16
Superstar = 1	0.16	0.36	0	1	0.23	0.42	0.31	0.46
Team Player = 1	0.31	0.46	0	1	0.24	0.43	0.15	0.36
Creative = 1	0.30	0.46	0	1	0.37	0.48	0.44	0.50
Relies on Science = 1	0.40	0.49	0	1	0.39	0.49	0.41	0.49

Notes: The table presents summary statistics for three groups of inventors: 1. those who have any firm-matched patents and are never recorded as deceased (‘Alive’), 2. those who are deceased within 30 years of their first career year whose deaths were not preempted and who do not patent substantially after death (‘Deceased 30’), and 3. those who are deceased within 30 years of their first career year whose deaths were not preempted, who do not patent substantially after death, and who have firm-matched utility patents before their announced death (‘Core Sample’). Career age for non-deceased inventors is calculated by years between first and last observed patent application. Human capital indicator variables are defined via quantile cutoffs within an inventor’s primary CPC class. Superstar is a binary variable measuring whether an individual inventor is particularly prolific in patenting, produces highly cited patents, or produces patents with high value. It takes the value one when an inventor is at the 95^{th} percentile or above within the inventor’s primary CPC technology class of numbers of patents produced per year, of mean citations or mean technology-cohort weighted citations to patents over five years following patent grant, or of mean value overall or per person for patents while alive, and otherwise is zero. Team player measures experience with teamwork and takes the value one when an inventor is in the top quartile of average patent team size within primary CPC class. Creative is a measure of the novelty of an inventor’s patents and takes the value one when an inventor is in the top quartile of new terminology embedded within their mean patent or in a single patent based on the Watzinger and Schnitzer (2019) dataset. Reliance on Science measures the extent to which inventors rely on science in producing patents and is based on an inventor being in the top quartile of the mean and max of the ratio of scientific citations to total science and patent citations across the inventor’s patents, and is based on the Marx and Fuegi (2019) dataset. Num. deceased patents indexes patents which identify any inventor as deceased.

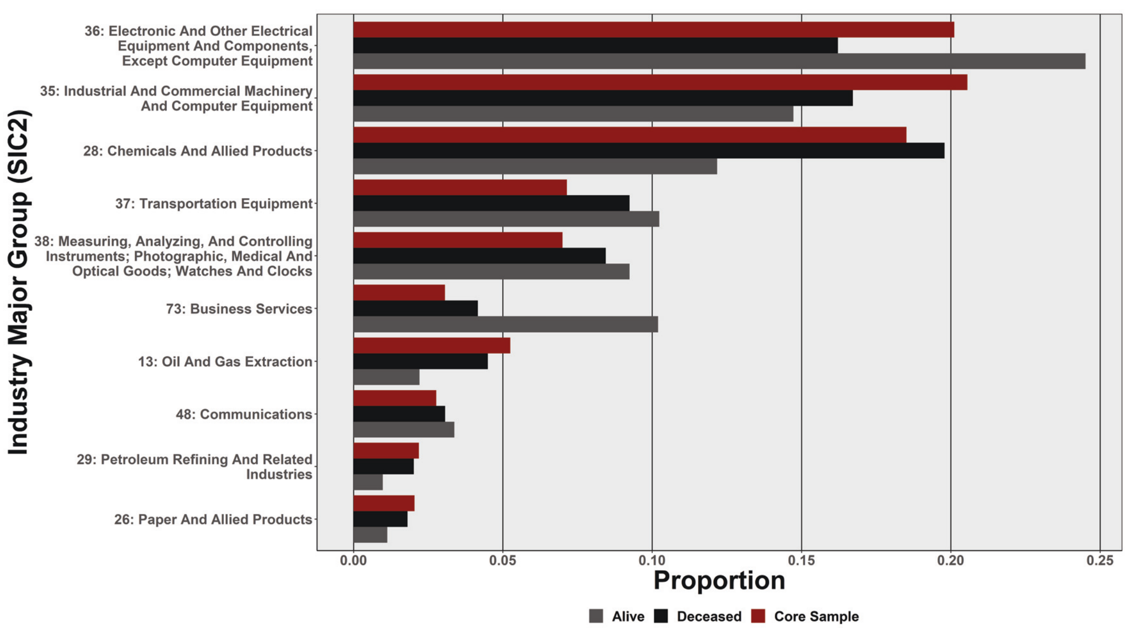
inventor population has a longer career age, fewer patents per year but of higher quality based on citations, and in general produces patents approximately twice the value of the population of living inventors. With respect to human capital heterogeneity, the deceased inventor sample includes a proportionally greater population of superstars (23% vs. 16%) and creative inventors (37% vs. 30%), while indexing proportionally fewer inventors with extensive teaming experience (24% vs. 31%). When considering the core sample relative to the population of non-preempted deceased inventors, the core sample indexes inventors with longer career age, and which produce more cited patents and more highly valued patents (just under four times the value of the average patent among living inventors). Regarding heterogeneity, this subsample indexes proportionally more superstars and creative inventors than the other two samples, and fewer ‘team players’.

To provide some sense of the sample of relative technical and industry sector experience of inventors, Figure 1.2 displays for each of the three distributions the proportion of inventors according to their top CPC technology class (Subfigure a) and according to their top SIC industrial major group (Subfigure b).[12] Relative

[12] Inventors’ top technological patent class is the most frequent Cooperative Patent Classification system (CPC) section affiliated with an inventor’s patents, and inventors’ top market sector is defined by the most frequent NAICS



(a) Inventor Top Technological Class



(b) Inventor Top Industry Major Group

Figure 1.2: Top Inventor Industry and Technological Patenting Class by Inventor Type

Notes: Subfigure (a) displays the proportional distribution of inventors' top technology patenting class - defined by the most-frequent top-level Cooperative Patent Classification system section which characterizes an inventor's patents - across all such technical classes. Subfigure (b) displays the proportional distribution of inventors' top industry - defined by the Standardized Industrial Classification 'Major Group' (SIC2) with which the inventors' patent assignees are most frequently affiliated - for the 10 most frequently observed industry classes.

to the sample of 'alive' inventors, the deceased subsets are overrepresented to a large degree in chemistry and metallurgy patenting (e.g. pharmaceuticals), while being underrepresented in patenting related to physics and electricity (e.g. electronics, computer technology). Likewise, in industry sectors, the sample of deceased inventors and their matched firms are over-represented in industrial and commercial machinery and computer equipment, in chemicals and allied products, as well as in oil and gas extraction major groups, while being under-represented relative to the distribution of 'alive' inventors in electronic equipment unrelated to computer technology. Despite these differences, however, the rank order of technological classes and industry major groups is relatively stable across the distributions, providing reassurance that the selected sample is representative for analysis.

1.3 Main Results: The Mean Value of Inventors to Firms

I now turn to the first question: what is the value of innovators to firms? To answer, I estimate the short-run stock market asset valuation of human capital. This section first outlines an estimator for inferring human capital asset value based on stock returns at patent grants and then applies the estimator to infer the value of human capital assets based on the *difference in valuations* for patents granted when an eventually-deceased inventor is alive and those announcing that the inventor is deceased. Robustness results are subsequently presented. These analyses are conducted on the 'core sample' of inventors and patent values are derived following the methods of Kogan et al. (2017).

1.3.1 A Model of Patent Signals and Human Capital Asset Values

Below, I outline a model demonstrating how patent grants reveal the value of inventor human capital via signaling of inventors' 'deceased' status and the corresponding quantity to be estimated.[13]

First, take as granted that a patent j conveys information about two assets of value to the firm: the grant of an intellectual property right with some inherent technical value, (ξ_j), as well as the status of inventor i human capital assets contracted by the firm, ω_{ij}. Formally, the asset value associated with patent

SIC major group with which the inventors' patents are associated. Ties are resolved via random assignment.

[13] For notation, Greek letters are leveraged to reflect potentially estimated econometric parameters whereas capitalized alpha-characters indicate random variables.

j is

$$AV_j = \xi_j + \sum_i^I \Delta\omega_{ij}$$

The goal of the current analysis is to estimate the population mean of the second term, $\overline{\omega}$, interpretable as the asset value of a given inventor.

Further assume that the market receives two types of patent signals, a signal of patent application and a signal of patent grant, and that the market awards to the firm asset value based on inferences from both signals. At and after application, firms are well known to publicize the technical information embedded within the patent application as firms seek to market future possible intellectual property assets (Kogan et al., 2017). Consequently, even though patent applications are not immediately publicly available[14], the market learns over time of a patent's potential asset value[15] and prices this asset value into the assignee firm's valuation. As a result, following application firms are awarded a market value $V_{j,app}$:

$$V_{j,app} = \pi_j \cdot \xi_j + \sum_i^I \Delta\omega_{ij}$$

where π_j is the market's anticipated probability of the grant of patent j. Given this 'perfect observability' of asset value subsequent to application, the market resolves at grant the residual uncertainty about the patent's success and then awards to the assignee firm the remainder of its intellectual property technical asset value as well as an adjustment for novel information regarding the human capital assets of the firm:

$$V_j = (1 - \pi_j) \cdot \xi_j + \sum_i^I \Delta\omega_{ij}$$

Given this signaling framework, there exist two distributions of patent grants - those which signal one or several un-preempted inventor deaths $V_{j,D}$, and those which do not, $V_{j,A}$.[16] In the latter case, the patent

[14]Historically in the United States, patent applications have either been withheld from publication until after the grant of a patent (prior to the 2001 American Invents Act) or published with some delay, statutorily 18-months (post-America Invents Act). Patent assignees may request that patent applications are revealed before expiration of the 18-month window, but this practice is an infrequent exception to the default of no early publication.

[15]As Kogan et al. (2017) noted, "anecdotal evidence suggests that the market often had advance knowledge of which patent applications were filed, since firms often choose to publicize new products and the associated patent applications themselves" (Kogan et al., 2017, p. 673). This perspective aligns with my interview with the financial trader who noted being aware in advance of pending patent applications via third-party news services providing information on industry patent applications and grants.

[16]Given no change in human capital assets signaled by a patent grant, $AV_j = V_{j,app} + V_{j,A}$

grant only resolves grant-based uncertainty regarding the technical value of the patent, whereas the former signals information regarding losses to the firm's human capital assets:

$$V_{j,A} = (1 - \pi_j)\xi_{jA}$$
$$V_{j,D} = (1 - \pi_j)\xi_{jD} - \sum_{i}^{I} \omega_{ij}$$

Under this structure, an estimator of the mean asset value of inventor human capital, $\overline{\omega}$, is directly computed as the difference in grant award distribution moments normalized by the average number of deceased inventors per patent among deceased patents:

$$\overline{V}_A - \overline{V}_D = (1 - \hat{\pi})(\overline{\xi}_A - \overline{\xi}_D) + \sum_{i} \overline{\omega}_i$$
$$\overline{V}_A - \overline{V}_D = \sum_{i}^{I \in D} \overline{\omega}_i$$
$$\frac{(\overline{V}_A - \overline{V}_D)}{(\overline{n}_{i \in D})} = \overline{\omega}$$

where $\hat{\pi}$ is the estimated unconditional probability of no grant[17], $\overline{n}_{i \in D}$ is the mean number of deceased inventors indexed per 'deceased' patent[18] and $\overline{V}_A$ and $\overline{V}_D$ are means of the respective grant award distributions. Crucially, this estimation assumes equivalence across the patent distributions of mean technical values (i.e. $\overline{\xi}_A \approx \overline{\xi}_D$) and of mean propensity of grant (i.e. $\overline{\pi}_{j,A} \approx \overline{\pi}_{j,D} \approx \hat{\pi}$). While these quantities are unobservable, these assumptions seem supported based on the characteristics of the patent distributions. The distributions exhibit similar citation properties (see Table 1.2) suggesting similar quality in patents, and the corresponding inventors exhibit a discrete, sudden shock in patent grants following the indexed death, which suggests that their patenting efforts likely did not vary in substantive ways in advance of their deaths (see Appendix Figure A.3).

[17]The estimate of $\hat{\pi}$ is derived from Carley et al. (2015), who approximate that the unconditional probability of a successful conversion from application to grant is 56%

[18]$\overline{N}_{i \in D}$, the mean number of inventor deaths, is directly observable in the data and varies depending upon patent events sampled. For the core sample, $\overline{N}_{i \in D}$=1.004 and this is the number leveraged in most analyses. When the patent sample varies, this variable also varies according to the characteristics of the patents examined, however, this variance does not drive significant change in outcomes. For the population of all patents announcing inventor deaths, $\overline{N}_{i \in D}$=1.007, and for the population of utility patents announcing inventor deaths $\overline{N}_{i \in D}$=1.008.

Estimating Patent Asset Values

Given the estimator for $\overline{\omega}$, what remains is to compute asset valuations based on patent grants. I do so using the approach outlined in Kogan et al. (2017). In Appendix A.3.1, I recap briefly the estimation approach and assumptions and refer the reader otherwise to that study for additional details.

Table 1.2: Patent Value Statistics By Type

	Deceased Inventors' Patents, No Death Signal (N = 4,848)				Deceased Inventors' Patents, Incl. Death Signal (N = 1,279)				Kogan Et al.
Moments:	C	$\frac{C}{\overline{C}_{tw}}$	ξ	ξ_{pi}	C	$\frac{C}{\overline{C}_{tw}}$	ξ	ξ_{pi}	ξ
Mean	19.34	0.99	58.84	36.11	17.95	0.83	17.50	7.38	10.36
Std. dev.	38.13	1.36	456.08	386.47	41.18	1.40	62.00	28.31	32.04
Percentiles									
p1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01
p5	0.00	0.00	0.01	0.01	0.00	0.00	0.01	0.00	0.04
p10	1.00	0.00	0.05	0.02	0.00	0.00	0.03	0.01	0.11
p25	3.00	0.20	0.62	0.26	2.00	0.09	0.30	0.09	0.73
p50	9.00	0.59	4.94	1.98	6.00	0.39	2.24	0.66	3.22
p75	20.00	1.28	31.56	13.71	18.00	0.99	10.59	3.80	9.09
p90	42.00	2.31	124.07	58.59	45.20	2.05	41.32	16.92	22.09
p95	72.00	3.24	212.58	120.14	67.00	3.09	77.33	33.41	38.20
p99	186.53	6.89	590.58	355.41	180.10	6.66	223.40	105.03	121.39

Notes: The table presents distributional statistics on estimated patent values and patent publication event returns for patents invented by the core subsample of 686 inventors. The first set of columns corresponds to the distribution of all deceased inventor patents over the inventor's lifetime granted prior to the first grant signaling an inventor's death. The next set of columns correspond to the distribution of all deceased inventor patents that signal the death of the inventor, but that are not preempted by a published patent application also announcing the death of the inventor. Of these patents, 683 patents are identified as the first patents to signal an inventor's death. The final column provides comparison patent values from the last column of Table 1 in Kogan et al. (2017), calculated over a sample of CRSP-matched patents from years 1926 - 2010 (N = 1,801,879), which are rescaled here to 2012 dollars for comparison. C indexes forward citations to patents. $\frac{C}{\overline{C}_{tw}}$ indexes 5-year citations scaled by the mean citations accrued over five years to patent cohorts granted in the same year and within the same 3rd-level CPC tech class. ξ indexes inferred patent asset value (AV) in 2012 hundreds of thousands of dollars. ξ_{pi} is the inferred patent value per inventor on the patent.

Table 1.2 shows key distributional statistics regarding the patent signal values estimated[19] for the 686 deceased inventors of interest, dividing the patents into two types: (1) those that lack an announcement of an inventor death ('Alive' patents), and (2) those that announce inventor deaths ('Deceased' patents). The table additionally shows the equivalent point estimates from Table 1 of Kogan et al. (2017) for a general comparison to a majority sample of the population of patents ever produced. In this table, C and $\frac{C}{\overline{C}_{tw}}$

[19] In the table, patent values are calculated based on buy-and-hold abnormal returns (BHARs). However, approximately equivalent results are also obtained throughout the paper when computing estimates via calculation of cumulative abnormal returns (CARs). See Appendix A.3.1 for formulas.

represent citations and 5-year technology-class-weighted citation indices respectively, computed from the PatentsView data.[20] In the table, ξ is the computed asset value of the patent assuming the market does not respond to human capital information in the patent (i.e., $\omega_{ij} = 0$), and ξ_{pi} denotes the per inventor estimate.

The results illustrate two patent samples that are similar to each other in distributional characteristics. Estimated means are well within a tenth of a standard deviation from one-another for citations and technology-weighted citations. Additionally, the samples exhibit rough similarity in computed per inventor value at the lower end of distributional percentiles (at and below the 50^{th} percentile).

However, the 'Alive' and 'Deceased' samples significantly vary in two ways. First, patent values substantially deviate in their means as a result of significant deviations in the right tail of their estimated value distributions. Estimated ξ and ξ_{pi} substantially diverge above the 50^{th} percentile of the relative distributions, with patent grants without a death announcement exhibiting greater values. Second, the distribution of patent values from Kogan et al. (2017) and the deceased inventor patents that do not announce an inventor death exhibit significant differentiation in the right tail of the distribution, with the Kogan estimates consistently falling between those of the two signaling types. These summary statistics are suggestive of the impact of human capital losses, given that quality (as conveyed via citations) appears relatively stable across the distributions but estimated technical value differs substantially for 'alive' patents as opposed to 'deceased' patents.

1.3.2 Findings: Inventors are Valuable Assets, on Average

Readily apparent in the distribution of the two patent types is the significantly greater value assigned to patents which do not announce an inventor's death. Figure 1.3 evaluates this relative difference by showing the quantities of interest, the mean of firm asset value awarded at grant for all inventor-patent level observations of each type normalized by the number of deceased inventors, based on the comparison of the two key distributions in Table 1.2.

In Figure 1.3, the mean asset value at patent grant assigned to the patents signaling inventor death is visibly lower than that of the 'alive' group of patents (\$786 thousand vs. \$2.6 million USD, respectively),

[20] Patent citations are well known to vary by the technological class of the patent as well as the patent's grant cohort. Accordingly, the standard practice in the literature is to weight citations by technology class and grant year. See Appendix A.3.3 for explanation of how technology-class weighted citation indices are calculated.

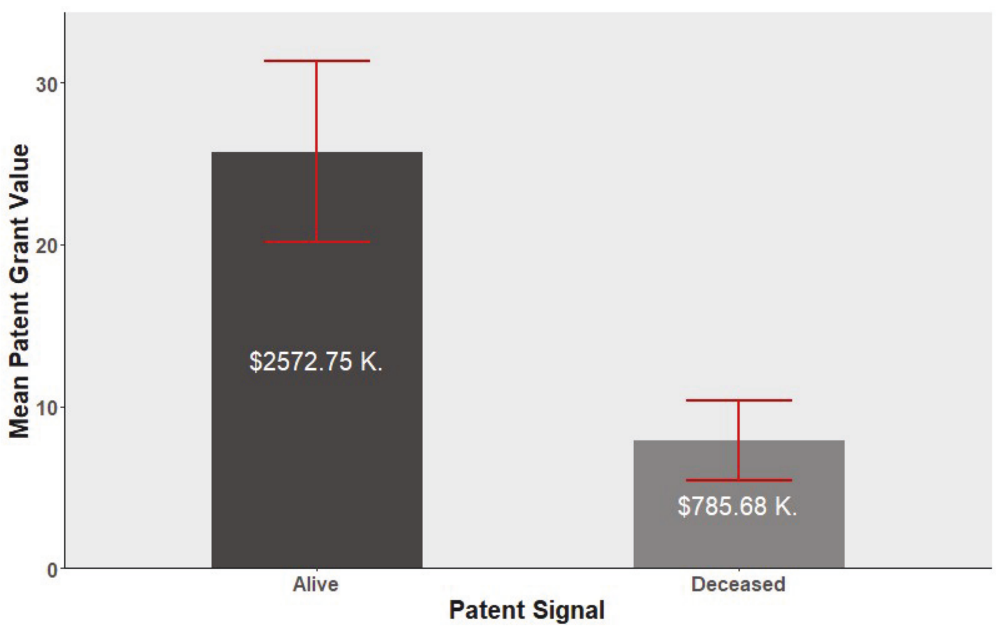


Figure 1.3: Mean Value Awarded at Patent Grant by Signal Type

Notes: The figure presents the mean dollar value assigned by the market over a three-day period following patent grants (t=0 to t=2) to the distribution of firm-matched patent-inventor observations of deceased inventors which do not signal an inventor death ('Alive', black) relative to those which do signal an inventor death ('Deceased', grey). Values reflect the value awarded at patent grant (V_A and V_D) and are normalized by the average number of deceased inventors per deceased patent in the sample. The bars are accompanied by 95% confidence intervals (red) on dollar value. Outcome is measured in 2012 dollars in 100,000s. This is computed for the 686 inventors which comprise the core sample, and only for the patents which first announce their deaths. Similar estimates are derived when preempted patents are included as well as when the sample of deceased patents is expanded to include all patent grants announcing an inventor's death. Estimation relies on event-window returns computed as 'Buy-and-Hold' aggregates of daily abnormal returns over the period, where abnormal returns are the difference between the firm's daily return and the market index (in CRSP, the value-weighted index [VALRETD]). Quantitatively similar results are achieved with cumulative abnormal returns (CARs).

estimating a mean asset value of lost human capital of approximately \$1.79 million in 2012 dollars. This more than three-fold difference suggests that exogenous changes in inventive human capital account on-average for over two-thirds of the value of the average patent asset grant.

Table 1.3: Difference in Patent Value Moments

Within Dimensions	$\overline{V_A} - \overline{V_D}$	$\frac{(\overline{V_A}-\overline{V_D})}{\overline{\xi_A}\times N_d}$	Test Values		
Mean Statistics			*t-p*	t 90% Conf. Int.	
Inventor	12.17	26.59%	0.05	1.94	22.39
Inventor, CPC1	11.56	25.60%	0.04	2.49	20.63
Inventor, CPC1, SIC1	11.78	25.45%	0.04	2.20	21.36
Inventor, CPC1, Firm	11.68	25.07%	0.05	1.73	21.63
Median Statistics			*MW-p*	MW 90% Conf. Int.	
Inventor	0.71	18.90%	0.00	0.47	1.12
Inventor, CPC1	0.71	18.95%	0.00	0.54	1.28
Inventor, CPC1, SIC1	0.55	16.35%	0.00	0.44	1.14
Inventor, CPC1, Firm	0.72	19.02%	0.00	0.51	1.28

Notes: The table presents the difference in patent values by patent grant signal type. The first four rows show statistics related to the patent distribution means, while the last four rows show statistics related to the patent distribution medians. Valuations are computed by constraining inventors and patents to those observations where the inventor is granted patents with both 'Alive' and 'Deceased' signals and by conducting a 'within inventor' paired comparison, where the mean of an inventor's 'Alive' patent grants is compared against the estimated value awarded at grant to the first patent announcing an inventor's death. The distribution of 'Alive' patents is further constrained to match the 'Deceased' patent in technological-class (CPC1), industry (SIC1) and individual CRSP firm. The first column, $\overline{V_A} - \overline{V_D}$, is the difference in distribution moments. The second column, $\frac{\overline{V_A}-\overline{V_D}}{\overline{\xi_A}\times N_d}$ is the estimate of the percent of asset value associated with an inventor's human capital on patents. The last three columns contain (1) the p-values from paired significance tests for difference in moments, and (2) corresponding 95% confidence intervals. Student's t-test for difference in means is indicated by t and MW indicates Mann-Whitney U-test. The results are robust at the 99.9% level for normalized difference test of means and for Moody's test of medians (unreported). Sample sizes are (where n_i indexes number of inventors and n_p number of patents): Within Inventor $n_i = 686$, $n_p = 5,531$; Within Inventor, CPC1 $n_i = 582$, $n_p = 3955$; Within Inventor, CPC1, SIC1 $n_i = 551$, $n_p = 3,602$; Within Inventor, CPC1, Firm $n_i = 530$, $n_p = 3,504$.

One concern regarding this estimate is that it does not control for the technical value of the patent, unobserved by the econometrician, and that the differences in the mean technical value of the patents may be driving the estimated effects. As a next step, I therefore consider whether the effect remains when controlling for the individual inventor (as opposed to just taking distribution means), controlling for patent technology class, and controlling for industry or firm with which the death is associated in time. Table 1.3 presents the results of computing the estimate via statistical tests on paired samples within inventor, within technology class, within industry, and within firm.[21] The results find that inventor human capital asset value is somewhat smaller, but still large and positive on average - between \$1.17 and \$1.2 million in 2012 USD. Considering median statistics shows that the asset value of the median inventor is significantly less than the mean - approximately \$55,000 to \$72,000. Taken together, these results suggest that the observed inventor asset valuations exhibit substantial rightward skew, as the average of the inventor asset value distribution is approximately 16 times that of the median.

For mean estimates, the results are significant at just around $p = 0.05$, with 90% confidence intervals based on a paired t-test estimating value in the most-controlled estimate (within-inventor, within-tech class, and within-firm) at between \$173 thousand and \$2.16 million in 2012 USD. Likewise, the paired Mann-Whitney-Wilcoxon median significance test estimates that access to the median inventor's human capital conveys to a paired firm asset value of between \$51 thousand and \$128 thousand USD at the 90% significance level. These results appear to be highly robust to the specification of sample restrictions, as they vary little between estimates despite substantial variation among patent and inventor sample sizes (the least-controlled sample corresponds to 686 inventors with 5,531 patents while the most-controlled sample corresponds to only 582 inventors with 3,955 patents). This suggests that the estimated asset valuations are likely not due to variance caused by technology class or firm effects which differ between patent assets, but due to the loss of human capital assets.

Of note, the estimated values of human capital are rather large relative to studies employing different methods (e.g., Giuri et al. 2007). This is likely due to the distributional assumptions embedded in the model of stock returns to patent grants. However, even if absolute patent values are overestimated, the relative proportion of the value of human capital should remain stable across the two distributions, suggesting strictly positive mean and median asset values for inventor human capital assets.

1.3.3 Robustness of the Asset Value Estimate

This section examines whether the asset values estimated are robust. Four potential threats to causal inference exist that may correlate with the observed differences and interfere with estimation of the asset

[21] Paired samples are achieved by differencing two quantities per inventor - the estimated mean of 'Alive' patent grant values compared against the estimated patent grant value of the first patent announcing the inventor's death. As each additional level of restriction is added, the 'Alive' sample of patents leveraged is limited to only those matching the characteristics of the 'Deceased' patent - in technology class, industry, and/or firm.

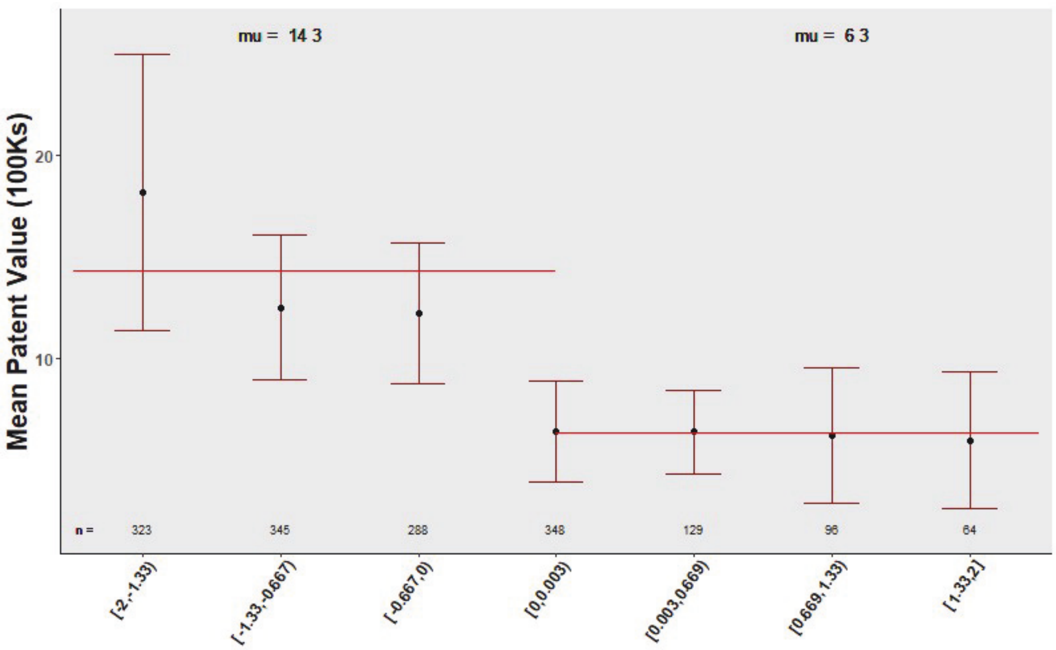
value of inventors. First is that the results observed may be driven by non-comparable patents or trends in patenting value unique to the distributions of inventors and which are not exogenous - in other words, I may be failing to capture truly exogenous variation in access to human capital due to inventor deaths. Second, it may be that the deceased inventor patents substantively vary in their intellectual property protection or propensity to grant due to their deceased status. Specifically, inventor deaths may drive up the time to patent and may erode the value of intellectual property rights assigned at grant as a function of timing but not of differing access to human capital. Third, the results observed may be driven by rightward-skewed extreme returns at patent grant that are only present in the 'alive' patent distribution, as patents are well-known to exhibit a long-tail, highly skewed distribution in quality and value. Finally, it may be that returns are improperly estimated due to a misspecified event-window. To ameliorate these concerns, I perform a few robustness checks.

Are Inventor Deaths Signals Exogenous?

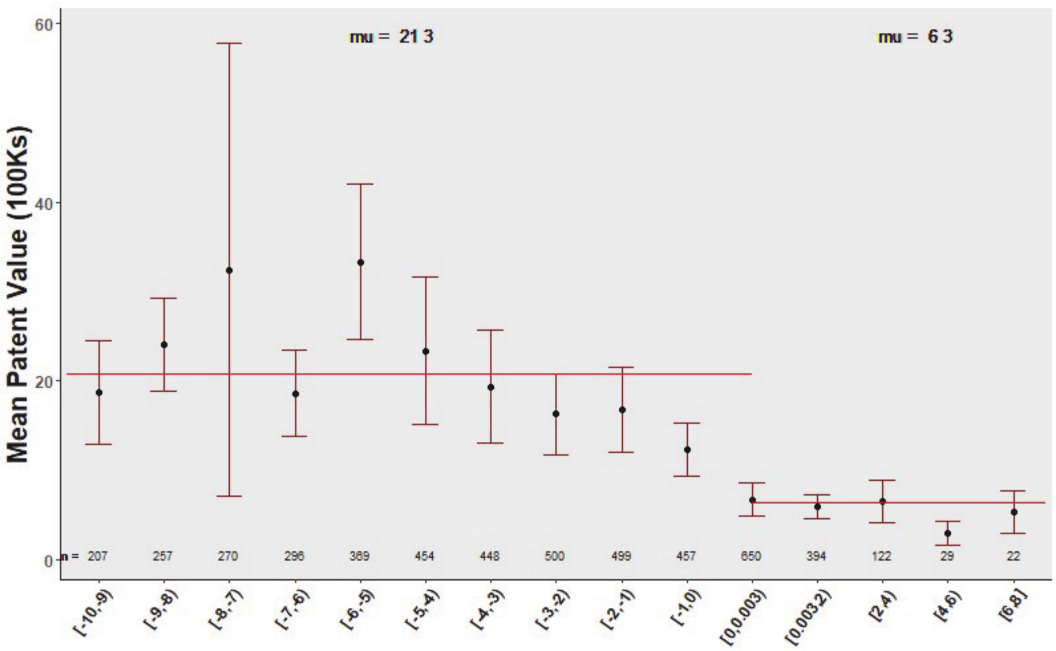
For the first concern, that inventor deaths may not be exogenous and that inventor-related career age and patent value trends or non-comparability may be driving effects, I first consider a regression-discontinuity-like robustness check where the estimated patent values at grant are compared for the relative distributions as a function of the time relative to death. For this analysis, I focus on the core sample of inventors and their patents inclusive of all patent grants signaling the inventor's death but for which the applications for the patents did not preempt the signal.[22] For these inventor-patent observations, I compute the mean value awarded at the patent grant according to event time bins indexing the days to grant.

Figure 1.4 displays the results from estimating these non-parametric means. To additionally control for team size in patent production, I estimate the difference in non-parametric means based on inventor asset value estimated on the per inventor asset value returns when the patent is granted. Subfigure (a) displays the results from computing patent grant valuation means per inventor across a short-run window of two years before the grant first signaling inventors' deaths to two years following that signal. Subfigure (b) is

[22] It is worth noting that while the earlier results focused on only the patent grants conveying the first notice of death for a given inventor, this sample is inclusive of patents signaling deceased status of an inventor after the first such notice. Patents are only omitted from the sample if the applications corresponding to that specific patent also lists the inventor as deceased and therefore the signal may already be priced in for that patent grant. Based on the qualitative interview and obituary search, I remain relatively unconcerned that the market tracks inventor deaths across patent grants.



(a) Short Run: t=-2 to +2 years



(b) Long Run: t=-10 to +8 years

Figure 1.4: Change in Patent Grant Valuation in Event Time

Notes: The figures illustrate the presence of a discontinuity in patent values in the time periods immediately proximate to inventor deaths. In each subfigure, point estimates are mean values of grouped patents based on event-time bins indicated on the x-axis. Whiskers reflect 90% confidence intervals. Subfigure (a) examines patent bins in the short-run of t-2 to t+2 surrounding an announcement of an inventor's death, while Subfigure (b) considers a longer-run analysis indexing t-10 to t+8. Sample sizes for each bin are located just above the x-axis in line with the point estimates, and grand means across the sample for the two patent types ('Alive' and 'Deceased') are located at the top of the figure.

similar but computes the estimated means across a window of ten years prior to eight years after the first signal of the inventors' deaths. In the figures, whiskers convey 90% confidence intervals on the estimated means, and red horizontal lines in the figures index the grand means by distribution.

The results show that patent grant valuations for the patents which announce inventor deaths suddenly decrease in value in-time with the announced death, and that the decrease in value is a discrete, negative shock to patent grant valuation. In the short-run analyses, patents invented in the two years preceding an inventor's death convey normalized asset value at grant of approximately \$14.3 million valuation per inventor and patents announcing death at and after the first signal of death convey a consistently estimated \$6.3 million valuation per inventor, implying that the asset value of inventor human capital estimated on this short-run window is approximately \$800 thousand in 2012 USD, slightly below the estimates in Table 1.3. Considering the long-run results illustrates that the sudden drop-off in patent grant valuation in the year of death persists in subsequent patent grants that identify the inventor as deceased. This suggests a lasting asset value decrease due to inventor loss. While there does appear to be a slight decrease in value in the year prior to announced inventor deaths in the long run figure - perhaps some small portion of inventor deaths are partly anticipated - the decrease in patent asset value in the year of death is still clearly distinguishable, and greater than \$400 thousand in 2012 USD in difference. This decrease in patent values on the cusp of the death event is significant at approximately the 90% significant level in both the short- and long-run analyses. The long-run analyses suggest a larger asset value for inventor human capital - approximately \$15 million in 2012 USD - which is in line with estimates derived without controls for inventor, technology class, or firm. Given the variation present and the nature of the discontinuity design, the true value of inventor human capital is likely closer to that produced by the short-run analysis and the earlier within-inventor results of between \$800 thousand and \$1.2 million in 2012 USD.

As a concern may remain that the inventor deaths examined include non-exogenous deaths, I additionally re-compute the estimated asset values from Table 1.3 based on a restricted sample of inventors exhibiting a substantially smaller career age of 15 years or less. The results for this analysis are presented in Appendix A.4.1 and estimate that inventor mean asset value is approximately \$490 thousand to \$573 thousand in 2012 USD, in line with the gaps on the cusp of the discontinuity graphs.

Do Death-Related Delays Weaken Intellectual Property Protection?

I next turn to consideration of whether deceased-inventor related delays significantly weaken the intellectual property protection afforded firms. As the length of intellectual property protection for patents in the United States is statutorily linked to the filing date of the original patent application, extended application duration may erode the value of patent grants. The presence of a delay generated by inventor death can be evaluated by fitting variations of this regression specification:

$$D_{jfy} = f_{poisson}(\epsilon_j fy;\ \beta_0 + \beta_1 \mathbb{1}(Death_{jfy}) + (\beta_2 \mathbb{1}(FirmMatch_{jf})\ or\ \gamma_f) + \gamma_{tech\times y,j})$$

where j is the patent, f is the corresponding firm, and y is the year of the patent. The dependent variable, D_{jfy}, is the number of days from patent application to grant, and the key independent variable of interest is $\mathbb{1}(Death_{jfy})$, a patent-level indicator for whether a patent grant announces an inventor death. Control variables include, $\mathbb{1}(FirmMatch_{jf})$, an indicator for whether patent j was matched to a firm in either the CRSP or Compustat databases, and fixed effects γ_f and $\gamma_{tech\times y,j}$, controlling for the effects specific to the permco firm to which patent j is matched as well as the NBER tech class characterizing patent j by application year.

Table 1.4 presents the results of fitting this specification. Column 5 specifically is estimated on the restricted sample of patents which are matched to CRSP permno data and which are also deceased inventor patents. The results indicate that the presence of any death announcement on a patent grant is associated with a 4.7%-11.14% increase in days to patent, with the real value likely close to the estimates of the preferred specifications (2) and (5) that control for tech class-by-year fixed effects and matching for the entire population of patents and that of deceased inventors' patents, respectively. When evaluated at the corresponding distribution means, these specifications suggest an increase in days to grant of between 4.70% and 6%, or 44.29 to 57.19 days.

Do these delays in patent grant explain the observed decrease in patent asset value attributed to lost human capital? Likely not. Given a mean time to patent grant for all patents considered in the analysis of 953 days, on average, patent grants award intellectual property assets for 20 years minus 953 days (6,352 days). Given straight-line depreciation, each day of the patent grant conveys average per-day asset value of roughly \$926 USD (based on the no-death announcement sample in this paper) or \$420 USD (based on the

Table 1.4: Time to Patent Grant as a Function of Death Announcements

	Dependent Variable: Days to Patent				
	All Patents		Deceased Inventor Patents		
	(1)	(2)	(3)	(4)	(5)
	[1.0829]	[1.060]	[1.1114]	[1.0515]	[1.0470]
Death Announced	0.0796***	0.0586***	0.1057***	0.0502***	0.0459***
on Patent	(0.0059)	(0.0049)	(0.0064)	(0.0054)	(0.0094)
	[1.0990]	[0.9934]	[1.0228]	[0.9589]	
Patent Matched	0.0944***	-0.0066***	0.0225***	-0.0441***	
to Firm	(0.0005)	(0.0005)	(0.0046)	(0.0042)	
	[905.06]	[35,326.90]	[914.80]	[10,995.05]	[4296.26]
Constant	6.8080***	10.4724***	6.8187***	9.3052***	8.3655***
	(0.0004)	(0.0798)	(0.0038)	(0.1200)	(0.2519)
Firm FE	No	No	No	No	Yes
Year X Tech Class FE	No	Yes	No	Yes	Yes
N. Obs	6,852,129	5,130,796	77,448	68,311	28,033
Log Like.	-1.0e+09	-5.0e+08	-1.2e+07	-6.9e+06	-2.6e+06

Notes: The table presents Poisson QLM fitted regressions of Days to Patent, the number of days between a patent application and patent grant, on Death Announced on Patent, an indicator for whether the patent announces an inventor death. Incidence rate ratios are in brackets and robust standard errors are in parentheses. Similar results are obtained in OLS regression on log(days to patent) as well as in negative binomial regressions. For the unrestricted sample of patents, the mean days to patent is 953.191 and the median number of days to patent is 805. For the sample of only deceased inventors' patents, the mean number of days to patent is 942.247 and the median number of days to patent is 784.
+ $p<0.10$ * $p<0.05$, ** $p<0.01$, *** $p<0.001$

estimates of Kogan et al. 2017). Accordingly, the delay comes at an effective cost of at most \$24 thousand to \$53 thousand, which is significantly below the estimated asset value of human capital.

Is the Asset Value only a Function of High-Value Outlier Patents?

Given the highly-skewed, long-tail nature of the patent grant value distributions, and the consequent highly-skewed distribution of inventor asset values, it is possible that the estimated differences in human capital asset value are entirely attributable to the presence of more extreme-value patents among those without a signal of death. To evaluate how sensitive the results are to outlier observations, I recomputed the estimates of human capital leveraging patent grant returns winsorized across the full distribution of estimated returns at the 95^{th} percentile level. Mechanically, given that the distribution of 'Alive' patents appears to have substantially more outliers than that of the 'Deceased' patents (see Table 1.2), winsorizing will compress the spread between the distributions. The results for re-estimating Table 1.3 are presented in Appendix Table A.4. Depending on whether the 30-year or 15-year career age sample of inventors is considered, the winsorized point estimates for mean inventor asset value are between \$52 thousand and \$104 thousand in 2012 USD, and the results are significantly identified at $p < 0.01$. As patent data is characterized in reality by rightward-skewed distributions, the earlier estimates of between \$400 thousand and \$1.2 million in 2012 USD are likely closer to the true asset value of mean inventor human capital for the sample. However, the current evidence is reassuring in showing that the results hold given the removal of outliers. Even when significantly winsorized, inventors are still estimated to have positive asset value at the mean and median of the inventor asset value distribution.

Are the Results Sensitive to the Event Window?

The study leverages the event window employed by Kogan et al. (2017) of a three-day grant period (t=0 to t=2). To assess whether the results are sensitive to the event-window, the inventor asset value estimates were recalculated leveraging event windows ranging from 2 to 6 days. The results are presented in Appendix Table A.6 and demonstrate that the estimated asset value does not function substantially as a result of varying the event window.

The reader is also advised to consider the results of Section 1.4.2, which explore whether firms are negatively impacted by inventor deaths in a 15-day window following the grant of patents with inventor deaths relative to those without.

1.4 Additional Results

This section focuses on two sets of additional results. The first considers whether asset value varies as a function of human capital types and industry. The second examines the larger sample of firm-matched patent records signaling inventor deaths and estimates the stock market response to news of inventor deaths over an extended 15-day period and under different models of market returns.

1.4.1 Heterogeneity of Human Capital Asset Value

I next turn to consideration of the remaining two questions: (1) Which types of innovative human capital are of more or less value?; and (2) To what extent does heterogeneity in value depend on industry?

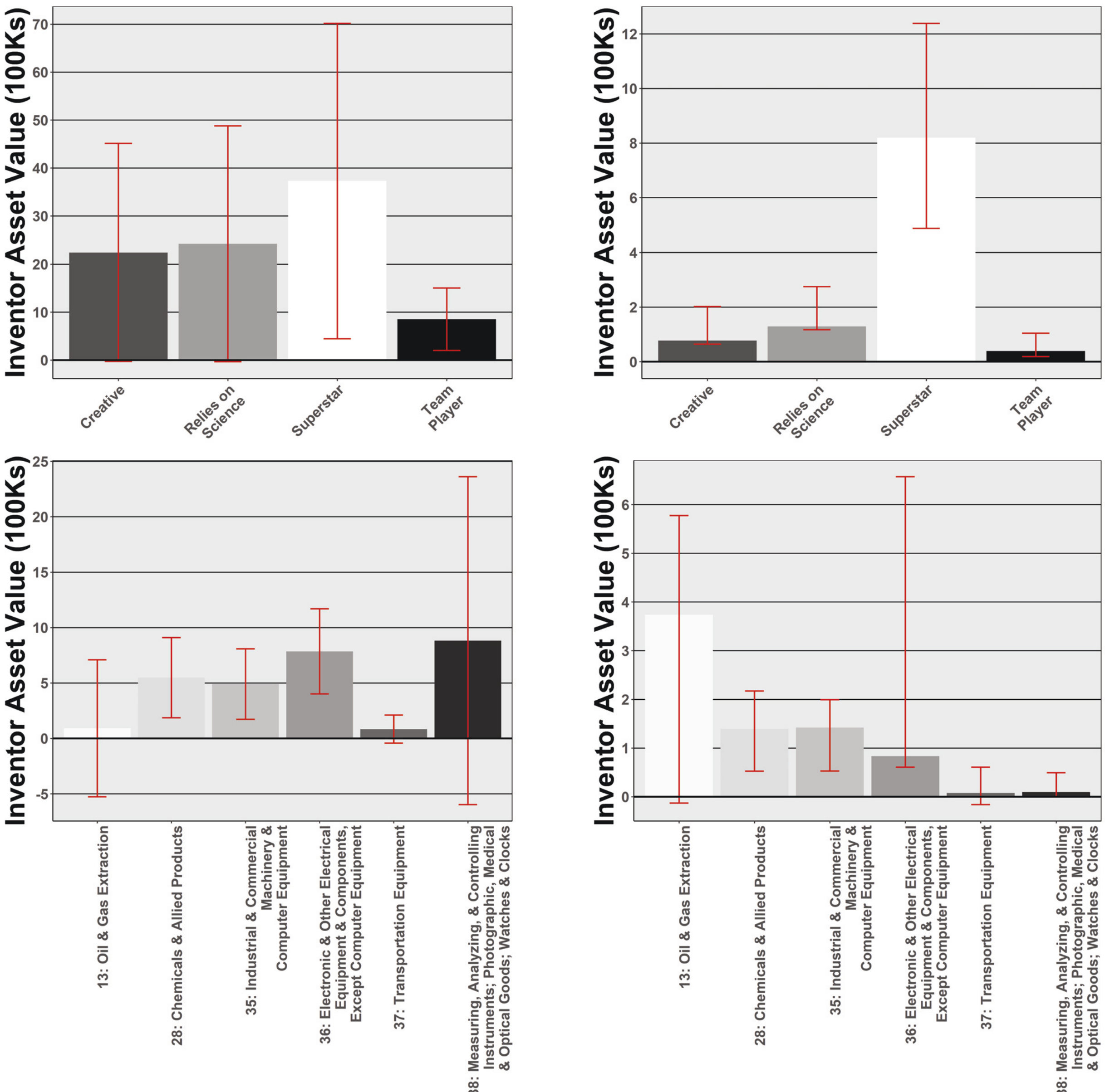
A likely reason for the large estimated value of human capital lies in the nature of the sample, which includes over-representation of superstar inventors and creative inventors relative to the total population (see Table 1.1). Superstars are likely measured at a higher rate than in the population of inventors for two reasons. First, because the sample requires firm matches, it focuses on data from large, public, and well-resourced firms that attract, recruit, and retain high-value human capital assets. Second, as the sample focuses on inventors who are identified as deceased and therefore likely exhibit a greater track record of patenting, the sample by nature will capture more prolific inventors.

Another potential explanation for why inventor asset value estimates may be overly large is that the value of human capital increases by the characteristics of innovators' projects. There is evidence that highly novel, less defined innovation problems are more prone to yield breakthrough performance returns, including among patents (Fleming, 2001; Stokes, 1997). Under such circumstances, human capital familiar with novel invention may exhibit a greater value. Given that the sample indexes a greater proportion of creative inventors than in the population, the anticipated asset value of human capital may exhibit additional skew characteristic of breakthrough invention.

Given these differences, I consider how inventor human capital heterogeneity may influence the estimated inventor asset value. Subfigures (a) and (b) of Figure 1.5 presents the result of estimating inventor asset value according to four inventor characteristic types that have been identified in the literature as relevant for

(a) Human Capital Types, Mean

(b) Human Capital Types, Median



(c) Industry Major Group (SIC2), Mean

(d) Industry Major Group (SIC2), Median

Figure 1.5: Heterogeneity in Inventor Asset Value

Notes: The figure displays estimates of the mean and median of inventor asset value by human capital type and by industry. Red whiskers indicate 90% confidence intervals (Mean estimates are based on t-tests, median estimates are based on Mann-Whitney-Wilcoxon estimates). Sample sizes (in number of inventors) for human capital types are: Superstar n = 214; Creative - n = 302; Team Player n = 103; Relies on Science n = 283; Sample sizes (in number of inventors) for industry major groups are: 13 n = 36; 28 n = 127; 35 n = 141; 36 n = 138; 37 n = 49; 38 n = 48; Industries were selected based on sample size of inventors, with inventor asset value estimated in all industries with 30 inventors or greater in the core sample.

invention. Superstar inventors are defined as those in the top 5^{th} percentile within the inventor's primary technological class of any of the following: (1) the mean or max value of patents produced among their 'Alive' patents, capturing monetary impact, (2) the mean number of citations or technology-weighted citations accruing to the inventor's patents within five years of grant, capturing quality, and (3) the mean patents produced per year, capturing prolificness. Team player inventors are defined as those who exhibit mean patenting team sizes in the top 25^{th} percentile among all inventors within the inventor's primary technological class. High novelty captures inventors who produce inventions that are characterized by novel properties, and is defined as those whose mean patent novelty scores or maximum patent novelty scores are at or above the top 25^{th} percentile across all inventors within their primary technology class.[23] Inventors who rely on science are identified as those that are in the top 25^{th} percentile of citations to science within their primary technology class.[24]

The figures reveal several interesting results. First, considering Subfigure (a), it is clear that superstar inventors convey significant value, but that this value exhibits potentially wide variance. 90% confidence intervals place the asset value of superstar inventors roughly between $500 thousand to $7 million in 2012 USD with a point estimate of approximately $4 million in 2012 USD. Aside from superstars, team players are identified to exhibit positive asset value, but interestingly are estimated to have asset value below the mean estimated for the average inventor in the sample. For the remaining two human capital types - creative inventors and inventors who rely on science - large point estimates are found, but these are just outside significance at $p < 0.1$ and are indistinguishable from null asset value. When considering the median inventor asset value (Subfigure b), all human capital types are found to exhibit significantly positive asset values. Superstar inventors again dwarf other human capital types in asset value, with a median superstar inventor asset value point estimate of $800 thousand in 2012 USD, while other asset value point estimates are all below $200 thousand. After superstars, the most valuable human capital types among the median inventor based on the estimates are reliance on science and then creativity, which are indistinguishable from one another in their confidence intervals, and then teamwork experience.

The figure also considers variation in asset value by SIC major groups, reflecting industry differences. Across both mean and median estimates, inventors are found to convey positive asset value to firms in

[23] This is based on the patent-level novelty scores produced in Watzinger and Schnitzer (2019)

[24] The data for this measure is drawn from Marx and Fuegi (2019).

industries related to chemicals, industrial machinery and computer equipment, and electronics. However, for the other three most populous industries, reflecting oil and gas extraction, transportation equipment, and measurement instruments, inventors are estimated to have asset values largely indistinguishable from zero.

The presence of indistinguishable from zero-estimates among both industry and human capital types may occur for potentially three reasons. First, sample sizes can be small. By-industry sample sizes are as few as 36 inventors in the oil and gas extraction industry. Given such small sample sizes, it is highly possible that point-estimates are inaccurate, and as a result they should be treated with caution. Second, it is also possible and likely that inventions in certain industries exhibit lesser value than other industries, due to less market demand for the technology developed. Given patents of lesser value, inventors of those patents will be estimated to have a lesser asset value to the firm. Finally, it is also possible that even in the presence of valuable technologies, there exists a lack of complementarities between inventors and technologies in some industries while complementarities exist in others.

Unfortunately, the present analysis is not well-powered or designed to distinguish among these three possibilities, and such investigation remains for future research. Further, particularly for human capital types, the present analysis is also unable to distinguish between the roles of selection and training in generating the estimated asset value links - it may be that the inventors studied selected into industries or human capital skill based on innate ability, or it may be that training and experience in industries or skills may increase an inventor's asset value independent of innate capability, but the current research design cannot distinguish between the two. The present results are therefore mostly suggestive of links between industry or human capital type and value that may exist and that remain to be confirmed.

1.4.2 The Market Penalizes Firms With Inventor Losses

The inventor asset value approach faces two main limitations. First, it requires focusing on variation among a small subset of inventors (the primary sample used in analysis comprises only 686 inventors) and as a result most information on deceased patent signals to the market are discarded prior to analysis. Second, it does not provide much information about the difficulties in replacing human capital and recovering from losses in the short run; it only estimates inventor asset value at the point of loss. Therefore, I next consider how the market impacts firm securities conditional on patent grants signaling inventor death over a longer duration. The advantage of this approach is that it allows for consideration of the impacts of the (much) larger set of deceased inventor signals, but this larger sample size comes at the expense of power in causal inference.

Specifically, I measure aggregated cumulative abnormal returns (CARs) over an event window inclusive of 16 days (t = 0 to t = 15) estimated from models of market reaction which allow for negative reaction to patent grant signals - a plausible assumption given that a signal of an inventor loss may represent a larger asset cost to the firm than the gain due to a patent grant. On a subset of 3,644 firm-matched patent grant events which signal an inventor death and 21,593 events without such a signal, I estimate the expected abnormal returns that accrue to firms and compare the difference in accrued abnormal returns. I do so via fitting a Capital Assets Pricing Model (CAPM, 'Market Model') and, for robustness, a Fama-French Plus Momentum Model (FFM). For the details of this analysis, the reader is referred to Appendix A.3.2.

Figure 1.6 summarizes the key finding of examining abnormal returns accruing only to the deceased patent signals. Following patent announcement, CARs exhibit a substantial and negative downward trend which persists throughout the event window and levels off at an approximate decrease of -0.025% in abnormal returns, suggesting that the market anticipates significant costs on firms after patent grants announcing human capital losses. These return effects are observed for both the first announcement of an inventor's death (Subfigure B) as well as the larger sample which includes subsequent death announcements (Subfigure A), with the larger sample exhibiting marginally more negative effects. This suggests that each announcement event draws additional market attention to firms' human capital portfolios and their corresponding losses.

Table 1.5 provides a more detailed version of these results and leverages returns from all firm-matched patent grant events without a death announcement as a control. Returns for both groups are computed for two windows — a 'runup' period estimating abnormal returns 10 days in advance of patent announcement, and an 'event' window period, estimating abnormal returns accruing to the firm stock for 16 days subsequent to the publication of patent grants. Column (2) indexes by-period CARs for patent grants without a death signal and column (4) indexes the CARs for patents that signal an inventor death. Columns (6) - (8) convey information about the significance of the difference in estimated CARs between the two signal distributions, with column (6) being the key column of interest. When considering $\Delta CARs$, it is clear that negative returns substantially accrue over time to firms for patenting events that announce inventor deaths relative to those which do not so. In the windows considered, these returns maximize at a -0.31% loss in market value reflecting a substantial equity value loss when considered relative to the context of publicly valued,

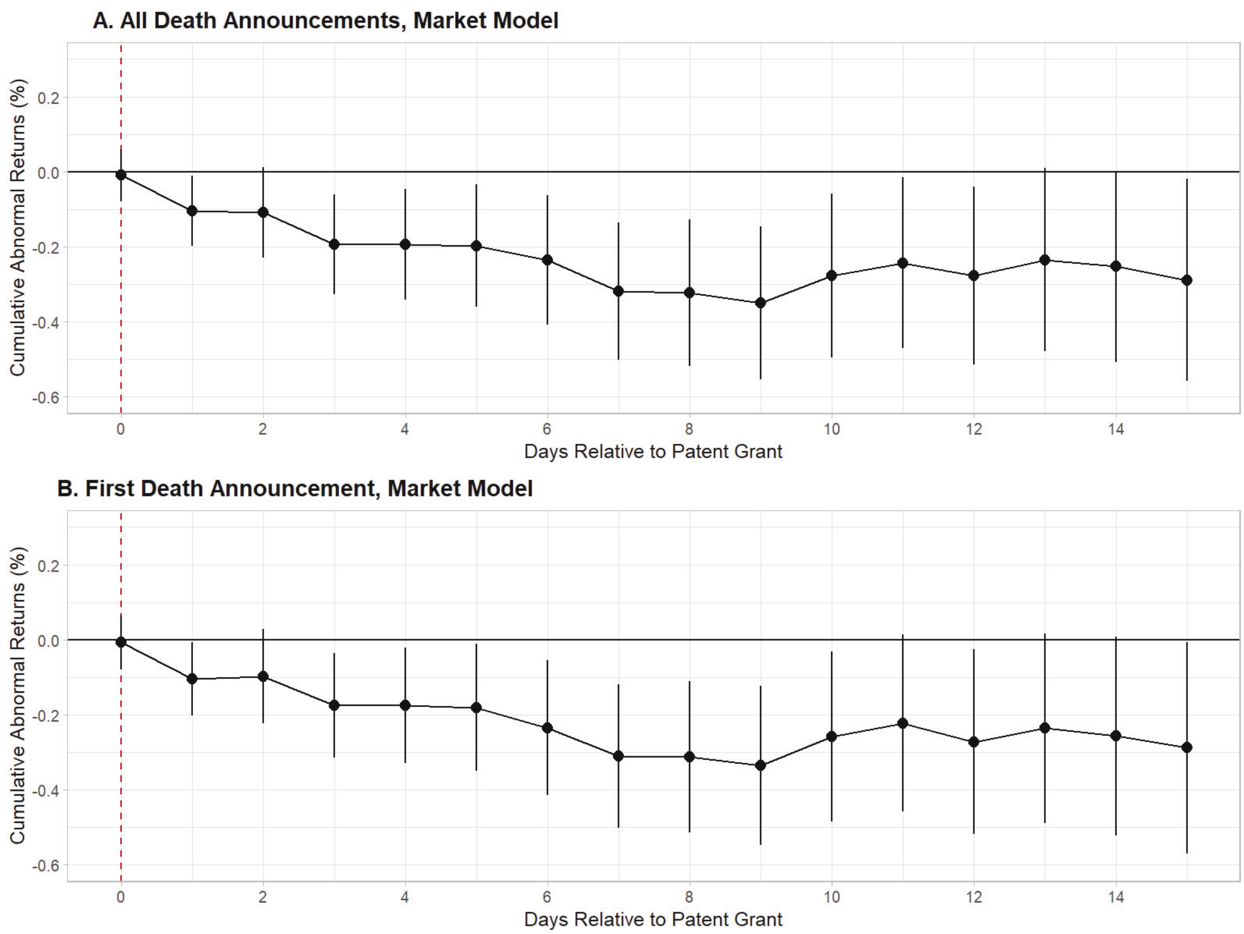


Figure 1.6: Cumulative Abnormal Returns (CARs) After 'Deceased' Patent Grant Events

Notes: The figure presents the mean cumulative abnormal returns (CARs) accruing to company securities in 1 to 15 day event windows following the publication of any patent with a deceased inventor announcement (Subfigure A) or the publication of only patents which first announce an inventor's death (Subfigure B). The data for Subfigure A consists of between 3,643 (event window t = 1 to 5 days) and 3,638 (event window t = 15) cumulative returns for patent publication events without missingness. The data for Subfigure B consists of between 3,401 (event window t = 1 to 5 days) and 3,396 (event window t = 15) cumulative returns for patent publication events without missingness. Abnormal returns are computed via a Capital Assets Pricing Model based on a pre-event estimation window indexing the time period [-150, -50], and requiring at least 50 observations per event for the estimation period. The estimation is robust to specifications of different models of returns. Calculating abnormal returns via the Market-Adjustment Model (AR = Return - CRSP's Value Weighted Index [VWRETD]) and via the Fama-French Plus Momentum (FFM) produces quantitatively similar results.

Table 1.5: Difference in CARs for Patent Grants with and w/out Inventor Death Signals for All Eventually Deceased Inventors During Runup and Event Windows

	Patents w/out Death		*Patents w/Death*				
Event Time	Mean CARs (%)	N	Mean CARs (%)	N	Δ CARs (%)	Std. Error	t-stat
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Runup Window Estimation							
-10	0.02	21,593	0.00	3,644	-0.02	0.02	0.78
-9	0.01	21,592	-0.04	3,644	-0.05*	0.03	1.80
-8	0.02	21,590	-0.03	3,644	-0.05	0.04	1.40
-7	0.01	21,589	-0.02	3,644	-0.03	0.04	0.63
-6	-0.01	21,588	0.02	3,644	0.02	0.05	0.50
-5	-0.01	21,585	0.03	3,644	0.04	0.05	0.75
-4	0.00	21,582	0.07	3,644	0.07	0.06	1.14
-3	0.02	21,581	0.04	3,644	0.02	0.06	0.33
-2	0.00	21,580	0.05	3,644	0.05	0.07	0.69
-1	0.00	21,579	0.06	3,643	0.06	0.07	0.87
Event Window Estimation							
0	-0.01	21,578	-0.01	3,643	-0.00	0.02	0.14
1	-0.01	21,578	-0.10**	3,643	-0.10***	0.03	3.20
2	0.00	21,575	-0.11*	3,643	-0.11***	0.04	2.84
3	-0.03	21,575	-0.19***	3,643	-0.16***	0.04	3.84
4	-0.04	21,574	-0.19***	3,643	-0.16***	0.05	3.30
5	-0.03	21,570	-0.20**	3,643	-0.16***	0.05	3.19
6	-0.01	21,569	-0.24***	3,642	-0.23***	0.06	4.17
7	0.00	21,569	-0.32***	3,642	-0.31***	0.06	5.34
8	-0.03	21,569	-0.32***	3,640	-0.29***	0.06	4.67
9	-0.04	21,569	-0.35***	3,639	-0.31***	0.07	4.75
10	-0.02	21,569	-0.28**	3,639	-0.26***	0.07	3.73
11	0.01	21,569	-0.24**	3,639	-0.25***	0.07	3.43
12	0.00	21,567	-0.28**	3,639	-0.27***	0.08	3.60
13	0.01	21,564	-0.23*	3,639	-0.25***	0.08	3.14
14	0.01	21,564	-0.25*	3,639	-0.26***	0.08	3.22
15	-0.01	21,564	-0.29**	3,638	-0.28***	0.09	3.24

Notes: The table presents the difference in cumulative average returns accrued (CARs) to securities with patent grants announcing inventor deaths relative to patent grants which do not announce inventor deaths. CARs are calculated across two windows, a 'runup' window estimating returns prior to the publication of the patent grant and an 'event' window following the announcement of the patent grant. The key column is Δ CARs, which indexes the difference in CARs accrued to securities granted patents without an inventor death and securities granted patents which announce an inventor death. Results are robust to: (1) whether estimated on the full sample of patents or restricted only to the patents with eventually deceased inventors, and (2) if estimates are computed leveraging buy-and-hold abnormal returns (BHARs). Abnormal returns are computed via a Capital Assets Pricing Model based on a pre-event estimation window indexing the time period [-150, -50], and requiring at least 50 observations per event for the estimation period. The estimation is robust to specifications of different models of returns. Calculating abnormal returns via the Market-Adjustment Model (AR = Return - CRSP's Value Weighted Index [VWRETD]) and via the Fama-French Plus Momentum (FFM) produces quantitatively similar results. N may be greater than the number of patents in the relative subgroups due to matching of patents to firms with multiple active securities. * $p<0.05$, ** $p<0.01$, *** $p<0.001$

innovation-active firms. In magnitude, these returns are greater than those estimated for patenting events in Kogan et al. (2017) (approximately a 0.07% return to patenting events) and are generally similar in magnitude to the ranges reported by Austin (1993) in that study of the positive returns which accrue to 20 large biotechnology firms due to patent grants. As negative CARs persist for the event window, the results suggest that the market penalizes firms for perceived inventor losses in a lasting way that anticipates long-run costs of inventor loss, and which suggests that frictions exist in replacing lost human capital assets.

Table 1.5 additionally provides evidence of the robustness of this difference in CARs. Inventor death announcements that represent the loss of a highly valuable asset should associate with negative returns subsequent to grant, while patent grants without such notices would associate with null or slightly positive market returns. In line with this expectation, patent events with death announcements exhibit large negative returns during the event window (column 4), while patent events without such announcements oscillate around a null effect (column 2). In advance of the patent grant, no substantial run-up in CARs is observed suggesting a lack of anticipation of inventor deaths as well as the exact timing of the patent grants themselves.

1.4.3 Robustness of Stock Market Results

The following three factors impede the interpretation of causal effects from event-study approaches: (1) the potential for event-anticipation; (2) the absence of well-balanced control observations; and (3) the potential for omitted events that are correlated in impact. While omitted events are unlikely to systematically correlate with the sheer volume of inventor deaths and patent grants, the first two concerns remain. To evaluate these concerns, I consider in Appendix A.4.2 robustness checks to evaluate the validity of these results. First, I demonstrate a lack of anticipation of inventor deaths in market movements regardless of whether the CAPM or FFM models are employed in analysis (Appendix Table A.7). Second, I produce evidence of a lack of abnormal returns surrounding application dates of patents announcing inventor deaths. This suggests that, at the point of application, the market does not learn substantial information indicating that the patent applications differ substantively in their value from otherwise similar patents without an eventual inventor death at the point of grant (Appendix Table A.8). Finally, I also demonstrate that non-aggregated event-time abnormal returns do not substantially vary from zero prior to patent grant events signaling inventor deaths, and that most individual market-day abnormal returns are negative subsequent to the patent grant (Appendix Figure A.4).

1.5 Discussion

The results of the present study show that innovator human capital is a high-value asset to the firm, such that an unexpected loss of inventor human capital generates market costs to firm equity. The average asset value of inventor's human capital to the firm is estimated to amount to approximately $400 thousand to $1.2 million in 2012 USD, depending on estimation approach. Similarly to patent assets, the results show that the distribution of human capital value is highly skewed, with relatively few instances of human capital accounting for much of the estimated value. Additionally, results demonstrate that the market penalizes firms that face inventor losses, with such firms facing a 0.1% to 0.3% negative cumulative abnormal return due to patent grants signaling an inventor death. This penalty suggests that the market anticipates lasting costs to the firm of lost access to the inventor's human capital. Such costs may come in the form of complementarities inside the talent pool or complementarities with intellectual property assets which facilitate the exploitation of the intellectual property.

The results also explore whether inventors' value to firms varies heterogeneously by human capital types or by industry. Unsurprisingly, superstar inventors are estimated to be particularly valuable for firms, with asset values of approximately $4 million in 2012 USD. Inventors with teaming experience are also found to have positive asset value, but this asset value is estimated to be less than that of the average inventor and is indistinguishable when considering standard errors. Additionally, the study identifies that certain industries exhibit positive asset values for inventors, while other industries appear not to. In particular, inventors appear to convey positive asset value in firms related to industrial machinery and computing, electronic components and equipment, and chemicals. However, the asset values of inventors in these industries are estimated at less than that of the asset value of the average inventor.

A back-of-the-envelope calculation facilitates conversion to estimates corresponding to the population of inventors. As patents invented by the primary sample of inventors studied are generally worth approximately 3.84 times that of the average firm-matched inventor in the data, the mean estimates suggest that the mean asset value of inventors in the larger population is closer to $104 thousand to $313 thousand in 2012 USD. Both estimates face limits, however, in that they are based on a sample of patents and inventors associated with publicly listed firms. Consequently, the associated firms are likely to be large, corporate entities with significant innovation resources and the capability to hire and attract high asset-value inventors. The estimated asset values identified, therefore, may not reflect the value conveyed by inventors involved in small firms or startup environments. Further, these large estimates are not unreasonable relative to the compensation typically received by such individuals. Jaravel et al. (2018) report annual salaries for a sample of inventors who actively patent in 1999 to 2012, and identify that the average inventor's annual salary is approximately $144 thousand in 2012 USD. Consequently, the back-of-the-envelope calculation suggests that the average inventor conveys asset value to associated firms of approximately 1-to-2 times the typical annual salary.

The contributions of the present study are three-fold. First, I report novel estimates of the asset value of innovative human capital and introduce a novel approach to estimating its asset values. These results contribute to previous literature that estimates the market value of innovations via analyses of firm financial returns (Kogan et al., 2017; Austin, 1993; Pakes, 2018; Hall et al., 2005; Nicholas, 2008). Importantly, while these prior assessments quantify the value to firms of patents as an intellectual property asset, the present study is the first to produce causal market-value estimates of innovator human capital. Second, I demonstrate that innovative human capital varies in value according to human capital type or skills. Previous studies on human capital and productivity identified positive benefits to various human capital types, such as general-use (Becker, 1975), firm-specific (Topel, 1991), and team-specific (Jaravel et al., 2018) human capital. However, directly placing an asset value on such human capital heterogeneity has been difficult, and the present results provide initial evidence on the value of such heterogeneity.

Third, the results contribute evidence in support of the knowledge-based view of the firm and related literature that suggests that human capital and human resource management are essential for firms' competitive advantage (Noe et al., 2017). While previous empirical evidence largely relies on correlational and survey-oriented results (e.g. Østergaard et al. 2011; Haneda and Ito 2018), this study demonstrates the causal link between firm reliance on differing types of innovator human capital and competitive advantage and long-run success.

The present study has several limitations. First, there is a concern about generalizability of the findings. I estimate the treatment effects in a sample of innovation-active public firms. While well-resourced public firms can recruit superstars at greater rates, which may drive the large point estimates identified, smaller and private firms (e.g. venture-backed startups) are more reliant on human capital and could be more sensitive to access to innovative human capital. Accordingly, relative magnitudes of asset value may be larger for such smaller firms and the results of the present study might not generalize well to smaller or private firms.

Second, the results are unable to distinguish the human capital benefits of selection and labor-market matching from training. Supporting the knowledge-based view of the firm, the results of the present study demonstrate a causal relationship between the talent of the firm and the firm's asset valuation. I find that firm reliance on innovator human capital is causally linked to equity, and that equity losses due to lost inventive human capital tend not to recoup in the short run, suggesting that losses of innovator human capital convey substantial frictions onto firms. However, while this hints at irreplaceability of human capital, I am not able to directly identify such irreplaceability or to distinguish whether the value of human capital types accrues solely through recruiting or also through training. The results say nothing about whether an innovator trained in novel production, for example, will increase the value of their subsequent patenting.

Third, the study is also poorly suited to identifying why human capital asset value may vary by industry. In addition to complications of small sample size, the current study has no approach for identifying whether variance in the value of human capital across industries is due to varying technological market value of innovation within industry or due to the presence or absence of inventor-intellectual property and innovation strategy complementarity. Both factors potentially explain why inventors might be more valuable in some industries than others.

The results also highlight meaningful directions of further research. In addition to sorting among the value-generating mechanisms discussed above, future studies may explore whether the value of innovative human capital varies among small firms, private firms, or start-ups. Other future research can also address the extent to which the value of differential skills, such as teaming capabilities or leadership training, moderates the value of human capital to firms. In this respect, one prediction could be that training in particular skills complements certain types of innovator knowledge or disciplines or industries (e.g., reliance on science might be particularly valuable for biochemists in pharmaceutical innovation). While the heterogeneity analyses of the present study contribute some evidence along this area of research, there is a clear need to separately investigate the importance of such training for firms' capacity to innovative.

Chapter 2

Migration Policy Reform and Global Collaborative Patenting within Multinational Firms: Causal Multi-country Evidence

2.1 Introduction

The economists' view on the geography of knowledge production for the multinational entity (MNE) is changing. The prior literature (see Hymer 1960; Caves 1971; Carr et al. 2001) argued that knowledge generating activities such as patenting should be conducted within the skilled-labor intensive headquarters country of an MNE, and that inventions patented at home could generate profits in foreign markets through foreign production alone. However, recent evidence, notably Foley and Kerr (2013), Branstetter et al. (2014), Miguelez (2018), and Kerr and Kerr (2018), documents a changing view of knowledge production within the MNE given rising international co-invention and global collaborative patenting by MNEs.[1] This view suggests

[1]MNE innovation is increasingly linked to international localization. Branstetter et al. (2014) document that MNEs from advanced industrial economies are largely responsible for the "exponential" growth in U.S. patents filed from China and India, such that "MNE sponsorship account[s] for the majority of new US patents granted to Indian

that technological development may depend on localization, as MNE innovation is increasingly recognized to rely on the MNE subsidiary and corresponding absorptive capacity. In this theory, the subsidiary acts as a moderator of the accumulation of 'sticky knowledge' (Cohen and Levinthal, 1990; Minbaeva et al., 2003; Minbaeva, 2007; Chang et al., 2012) or as a source of knowledge flows which rely on transferred human capital via short and cyclical movement (Gmur and de Sola, 2013; Kerr et al., 2016).

In particular, the cross-border mobility of inventors is highlighted as a key mechanism for global knowledge co-production by MNEs, but evidence of this relationship is thin.[2] Kerr and Kerr (2018) provide some evidence around how cross-border mobility of inventors facilitates the production of global collaborative patents and show that larger MNEs are more likely to engage in greater cross-border inventor mobility. Such results are of policy relevance and beg the question of how MNEs' globalized knowledge production and the costs of human capital migration are interrelated.

The purpose of this study is to explore that interrelationship. Specifically, we do so through investigating whether and to what extent MNEs' subsidiary-level investments in innovation change following migration reforms that ease barriers to immigration to a country. We match 14 business-travel-related migration policy reforms within 9 countries to the patenting activities of 9,179 MNEs and their country-level subsidiaries identified in the database of all USPTO patents in order to measure how shifts in the barriers to international human capital mobility impact the subsequent patenting of MNEs. To identify exogenous variation in these mobility barriers independent of MNEs' activities, we employ an exposure-based event study design, in which subsidiaries within a country are differentially exposed to reform events conditional on their historical dispersion of MNE invention activities. We find that long-term oriented pro-business reforms to migration policy significantly drive MNE investment within a country, increasing annual production of global collaborative patents (GCPs) therein by between approximately 0.5% and 2.1% on average. We additionally find

or Chinese inventors in recent years" (pp. 139-140, ibid.). Further, Kerr and Kerr (2018) cite analysis from the Bureau of Economic Analysis to state that the share of R&D for U.S. MNEs conducted by foreign subsidiaries rose from 6% in 1982 to 14% in 2004.

[2]Starting with Edström and Galbraith (1977), scholars have documented that geographic mobility of human capital enables multinational firms to transfer and exploit knowledge more efficiently in the intrafirm context than would be possible through external market mechanisms (Almeida and Kogut, 1999; Rosenkopf and Almeida, 2003; Oettl and Agrawal, 2008; Foley and Kerr, 2013; Singh, 2005; Choudhury, 2016). However, relatively little work examines how migration or migration policy influences the production of globalized inventions, and has largely focused on the importance of social ties for the management of global invention activities. Extensive literature examines, for example, cross-border ethnic ties as a key mechanism in facilitating global knowledge co-production as documented by Kerr and Kerr 2018, Saxenian (2002); Saxenian et al. (2002); Saxenian (2007), Kerr (2008) and Foley and Kerr (2013).

that these increases are substantially driven by large MNEs and by patenting activity increases among non-migrant inventors. These results provide strong evidence that inventor mobility causally facilitates MNEs' global production of inventions. We additionally show that significant spillovers occur subsequent to reforms, in which non-migrating inventors increase their relative investment in global collaborative patenting.

We first indexed the migration policy changes studied via a larger project that sought to collect all unilateral migration policy reforms and initiatives that shifted barriers to human capital mobility across 15 countries.[3] For the current study, we focus on the consequences of the 14 reforms identified to encourage 'long-term' or 'permanent' (i.e. 1 year+) business-travel enacted during the period of 2000 to 2013. We then merged to the reforms measures of the quantity of patenting activities (e.g. patent count indices) of 9,179 MNEs with a total 25,818 subsidiaries within the 15 countries. In our analyses, we consider patent outcomes of three types: (1) overall patent counts, (2) global collaborative patents, defined as those patents with a geographic footprint that crosses international borders, and (3) domestic patents. We also use fine-grained data on migrant inventors and their patents from the USPTO to measure how the changes in migration policy affect the cross-border mobility and consequent patenting of inventors. In doing so, we provide insights on the direct effects of migratory reforms on MNE-affiliated migrant inventors, and their subsequent patenting within MNE subsidiaries.

We conduct analyses leveraging an exposure-driven event study framework. Migration policy changes are treated as events that shock MNEs' production of inventions in the global context *vis-a-vis* shifting country-level barriers to cross-border human capital movement, and we measure how MNE subsidiaries within these countries change their patenting activities before and after the reform events. A key challenge for causal inference in this approach is that MNE subsidiary behaviors are not necessarily exogenous to the country-level enactment of migration policy changes – in fact, MNEs may anticipate such events and redeploy resources dedicated to innovation accordingly. To establish causal estimates of how MNE subsidiaries are affected by such changes, we therefore measure exposure to reforms via the historical dispersion of an MNE's innovative activity external to the subsidiary and show that this measure is positively associated with response to reform events.

The study identifies three main findings. First, we find robust evidence for reform-driven increases in

[3] Brazil, Canada, Chile, China, Germany, India, Italy, Japan, Mexico, the Philippines, Portugal, South Korea, Spain, Taiwan, and the United Kingdom

global collaborative patenting and overall patenting by MNEs, with annual subsidiary-level GCP production increasing by between 0.5% and 2.1% on average. Second, we show that a large portion of this increase is driven by long-term inventor migrants, but that such migrants account for fewer than half of the estimated marginal change in produced GCPs. Finally, we show that MNE response is heterogeneous, driven primarily by subsidiaries of large MNEs above the mean of MNE size and by reform spillovers onto non-long-term-migrant inventors.

These results contribute to three literatures. We first show that skilled migration is a key input to the production of global innovations among the modern MNE, and that MNEs invest in invention activity in response to policy changes that impact such movement. Here, we contribute to the nascent literature on international co-invention and the global collaborative patenting activities of MNEs (Kerr and Kerr, 2018; Branstetter et al., 2014) and are the first to show that this production of globalized invention by MNEs is causally dependent on the mobility policy context. Second, the results reinforce the importance of MNE subsidiaries for capturing and generating inventions and consequently emphasize the role of MNE subsidiary "absorptive capacity", particularly among large MNEs. This provides support for the knowledge-based view of the MNE, namely, that MNEs and their subsidiaries exist due to their ability to manage knowledge transfers in the face of international barriers to market transactions and the moderating role of subsidiaries in receiving and accumulating knowledge (e.g., Kogut and Zander 1992, 1996; Caves 1971; Cohen and Levinthal 1990) Finally, we contribute to a literature on the role of migration policy for innovation outcomes of firms and regions by shedding light on the implications of business-travel-related migration policy reforms on global and local innovation by MNEs. This adds nuance to prior research which outlines the implications of immigration policy changes for subsequent innovation via knowledge transfer and knowledge recombination (e.g. Borjas and Doran 2012, Moser et al. 2015; Hornung 2014; Choudhury and Kim 2019).[4]

We additionally highlight a data and a methodology contribution. For data, we collected and introduce with this study a novel database indexing 253 migration policy changes in 15 countries spanning the years 1893-2016, with an emphasis on the period from 2000 forward, and described in Appendix B.1.2. With

[4]In the broader field, other research presents evidence on migration patterns and their shifts over time (e.g., Kerr et al. 2016; Czaika and Parsons 2017) as well as the empirical implications of immigration for local labor market outcomes (e.g. Borjas 2004, 2009; Hunt and Gauthier-Loiselle 2010). Even within the larger field, this study is one of the first to estimate effects across multiple countries and multiple events as opposed to engaging in 'case study' analyses.

regard to methods, we outline an empirical approach for dealing with the econometric difficulties imposed by high-frequency events which are proximately clustered over time and for estimating causal effects given such settings.[5]

The remainder of the paper is organized as follows. Section 2 reviews the empirical context examined (migration policy reform events impacting business-related migration), the data constructed for estimation, and the identification strategy. Section 3 outlines the core analyses and presents main results. Section 4 then provides an overview of the robustness of the results via several different approaches. Section 5 then concludes.

2.2 Data Sources and Empirical Strategy

Our analysis measures the variation in MNE subsidiary patenting caused by subsidiary-level exposure to business-related migration policy reforms in the country of the subsidiary. We draw on two sources of data: (1) 14 reforms to migration policy impacting long-term business migrants during the years 2000 - 2013 and enacted within 9 countries drawn from a novel dataset we introduce indexing 253 such reforms across 15 countries, and (2) the patenting activities of 9,179 MNE assignees and their affiliated inventors indexed in USPTO patent data. To estimate the consequences of reforms, we employ in the data an event study design. For causal estimation, we measure the exposure of the MNE subsidiary to reforms via the historical scope of the MNE's innovation network, as the geography of historical inventive activities is likely predictive of exogenous variation in contemporaneous resources and capabilities necessary to take advantage of potential international collaboration post reform enactment.

[5]The context we study suffers from an embarrassment of riches of sorts – the frequency of reforms events is so high for some countries that several events of the same general type occur across several consecutive periods within some countries. This clustered nature of reforms limits estimation under classical event study methods, where current practice is to consider only events which are to some-extent isolated over time from other events. If the current study were to follow this practice and drop observations with consecutive reform events, we would quickly suffer from a loss of statistical power as our reforms are measured across only 15 countries and only occur within nine of the countries. Instead, we take steps to adjust event-study methods to deal with the closely time-clustered nature of the reforms and go to lengths to demonstrate the relative robustness of the estimation approaches we employ in the appendix.

2.2.1 Data and Summary Statistics

Migration Policy Reforms Dataset

Our main source of variation in the ease of MNEs' global patenting activities is the occurrence of country-level reforms to migration policy and migration-related programs that impact business-related inventor movement over the long-run. Specifically, we focus on estimating the effects of 14 reforms enacted during the years 2000 - 2013 that are anticipated to increase the ease of migration, either through increasing the rights or the expected volume of migrants on business-related travel conducted with potential stays of a period of a year or more.[6] The reforms, detailed fully in Appendix Table B.1, largely consist of changes to the enactment of migration processes which facilitate access to a country (e.g. standardization of visa application or entry procedures), restructuring of the immigration system to select on business-related travel or travel by high-skill migrants (e.g. implementing a 'point-based' system that selects for migrants with technical skillsets and with job contracts within country), and restructuring of the benefits received by foreign workers after entering the country (e.g. allowing for access to health benefits and facilities).

These reforms were identified as part of a larger project to construct a systematic index of all unilateral policy reforms and governmental programs instituted across 15 countries that were anticipated to drive changes in the migration patterns of high-skilled immigrants. This project is described in Appendix Section B.1.2. For the purposes of that project, we selected countries based on the presence of (i) historical enactment of intellectual property legislation supportive of patenting, (ii) multinational activity, and (iii) significant migration flows.[7] Following collection, the primary documents and sources describing the reforms were

[6]While we focus on 14 reforms enacted in 2000 - 2013, we identify 3 additional reforms enacted in 2014. We adjust analyses to account for these reforms. We focus on reforms enacted during 2000 to 2013 to evaluate shifts in the barriers to global patenting separate of global innovation trends and biases emerging in the pre-2000 period. During the 1980s and 1990s, the rate of granted global collaborative patenting at the USPTO increased rapidly while lagging substantially behind similar growth in single-country patent filings (see Appendix Figure B.1). Patenting rates rise significantly post-1980 (an increase that is well-documented in Kortum and Lerner 1999), but growth in global collaborative patenting trends substantially behind overall patenting, defining GCPs as a distinctively modern phenomenon. One explanation may be the standardization of international intellectual property rights in the 80's and 90's (Branstetter et al., 2006), which established an environment more conducive to global collaborative patenting as international collaborations entailed lower IP risk post-standardization. Standardization also increased the ease of reciprocal recognition of other countries' patents by the USPTO. Prior trends may therefore confound analyses, as they may correlate with opportunistic global MNE investments due to implemented I.P. standards and changes. We are constrained to analyzing effects through 2013 as the patent data leveraged face significant attenuation due to rightward censoring at that point.

[7]Ten of these countries coincide with the sample analyzed in Branstetter et al. (2006), who study the impact of systematic reforms designed to strengthen and standardize intellectual property on MNEs foreign direct investments between 1982 to 1999. We began first with those countries sampled in Branstetter et al. (2006) and expanded the

analyzed to derive their anticipated effects on the volume and rights of different migrant types. For the sample considered, we isolated specifically on reforms that impact business-related migration with a longer time horizon (one year or more).

Consider a few representative examples of the reforms: In 2009 and 2010, South Korea implemented substantial restructuring of the ways in which business migrants would access the country through the introduction of Contact Korea (2009) and the HuNet Korea Immigration Network (2010). Contact Korea is a program office codified in law and established within the Korea Trade-Investment Promotion Agency that is charged by the government with the mission of implementing programs to centralize and support firm recruitment of global talent. The functions of the office include identifying business and recruitment needs and opportunities as well as providing visa recommendation, immigration support, and relocation assistance. A year later, the government implemented HuNet Korea, a three-way platform that standardized business-related migration processes and digitally matched three groups: high-skilled foreign workers searching for employment, companies seeking those with technical skillsets, and the governmental system necessary for approving visa applications. The platform serves as a system for clearing business-related visas, where prominent members of the local business and political communities can nominate foreign migrants for a business-related visa, which would prioritize their applications within the migration approval system. The implementation of the HuNet reform additionally implemented a streamlined system for obtaining resident status within the country for both business-related migrants and their families. Together, these reforms established a cohesive platform for business-related migration with long-term stays into South Korea, promoting matching of employees and Korean firms through standardized processes and through facilitated access. These reforms are coded as promoting both the volume of business-related migration (e.g. through incentivizing migration directly) as well as the rights of such migrants (e.g. through facilitating paths to residency).

Contemporaneously, in 2010, the National Institute of Migration in Mexico standardized procedures and practices for immigration case officers via the introduction of a new manual for case admissions as well as SETRAM, the Electronic System of Migration Procedures. By introducing these systems, the government of Mexico introduced greater centralization into immigration decisions, removing uncertainty for future

sample to 5 additional countries with the aim of including countries that are the source and destination of significant migration flows.

Table 2.1: Timing of Permanent Business Reforms Examined

Country	Year of Reform
Chile	2005
China	2004
Germany	2005
	2012
Japan	2010
	2012
Mexico	2010
	2011
Portugal	2001
South Korea	2009
	2010
Spain	2003
	2009
United Kingdom	2006
Countries without reforms: Brazil; Canada; India; Italy; Taiwan; Philippines;	

Notes: This table provides information about the timing of reforms enacted in the countries in the study. The reforms selected are anticipated to increase forward migration and immigration due to business-related travel with stays of a year or greater. These effects are anticipated to occur through either increasing the volume of migration via directly incentivizing migration or through increasing the rights of migrants engaging in business-related travel and thereby yielding an indirect incentive to migrate.

migrants. A year later, the government enacted a major structural overhaul of Mexico's immigration system via the Migratory Act of May 25th, 2011, which explicitly sought to recognize migrants with business ties to the country who had previously fallen into irregular migration categories. As part of this overhaul, the law instituted two categories of immigration permits likely useful to migrants on business travel - visitor and temporary resident migrants. The former reform was expected to have increased the volume of migration (via standardization of entry procedures and resolution of entry uncertainty), whereas the latter systematic reform is anticipated to increase the rights of migrants engaged in business travel.

Table 2.1 displays the sequence of timing of the sample reforms. The 14 reforms exhibit some similarity in their characteristics. Of the 14 reforms, six involve the implementation of 'green card'-like policies which provide for long-run residence of migrants with work contracts, three policies involve the institution of points-related immigration policy elements that in some way favor business-related travel, and six reforms index efforts to integrate migrants or provide post-migration benefits, such as familial migration and access to local healthcare and education systems for migrants and their families. Additionally, three of the reforms involve complete overhauls of migration systems within countries and three primarily standardize application and entry procedures and decisions via new processes and electronic platforms.

MNE Global Patenting Activity

We merged the reform events to measures of the cross-country innovation activity of 9,179 MNEs. Specifically, we use data on patents granted by the United States Patent and Trademark Office (USPTO) to identify MNEs and to aggregate statistics on the patenting activities of MNE subsidiaries in countries enacting reforms.

We draw on all patents granted by the USPTO between January 1976 and December 2016 and indexed in the UCB Fung Institute patent data sample (Balsmeier et al., 2018).[8] In total, this constitutes over 6 million patent grant records. A unique quality of the UCB dataset is that it builds upon prior patent-firm matching efforts (e.g. the NBER patent project) and leverages a machine learning algorithm to disambiguate the individuals and organizations to which intellectual property rights are assigned, producing a match of patents to unique assignees.[9] Extensive prior work describes both the USPTO data and assignee disambiguation efforts (see Hall et al. 2001; Jaffe 2017; Balsmeier et al. 2018) as well as the role of patent data as an indicator of innovation (Trajtenberg, 1990; Hall et al., 2001). On the UCB dataset, we perform additional manual edits to correct the highest-frequency errors in patent assignee standardization (e.g. matching assignees with different formal names across geographies), in recorded patent grant and patent application dates (e.g. fixing transpositions in year records, such as 9180 as opposed to 1980) and in geography assignment of patents and inventors at the country level.

In the resulting matches of patents to standardized assignee identifiers, we then index the international 'geographic footprint' of each assignees' innovation activity and measure the quantity of these activities at the assignee-country level. For each patent, we aggregate the reported country of inventors and assignees affiliated with the patent[10] and produce aggregate patent counts at the assignee-country level.

[8]We draw on a sample of the data downloaded 10-25-18 from Google BigQuery. The data exhibit rightward censoring in matching, so we isolate to patent counts applied for through 2014.

[9]The UCB data are useful for measuring the geography of MNE innovation activities as the data (1) uniquely identifies organizations to which patents are assigned, and (2) indexes bibliographic data regarding inventor and assignee locations (Balsmeier et al., 2018). To identify standardized patent assignees across patents which list an assignee organization, the authors of the data employed a machine-learning based disambiguation routine that leveraged prior matches in the NBER patent project (Hall et al., 2001) to predict and assign to more recent patents a standardized assignee organization name and identifier. We build upon this disambiguation in our merged data through performing additional hand-coded standardization routines.

[10]Leveraging bibliographic data indexed for each patent in the sample, we geo-locate each patent's inventors and corresponding assignees at the country-level. By law, each patent filed with the USPTO lists all assignees who control the granted intellectual property rights of the patent as well as every inventor who was involved in the invention of the patented technology. For inventors, location information is listed typically at the level of city, state,

Once these counts are determined, we limit the data to a sample of likely MNEs and their subsidiaries using three criteria: First, we require that the assignees have produced any patents with an international footprint spanning multiple countries at any point - these compose the likely 'MNEs'. Second, we focus on only MNEs with patent production in the 15 countries researched to identify reforms - if we observe any eventually-produced patents applied for by MNEs with inventors or assignment in those countries during the years 2000 to 2014, we assume that an innovating MNE subsidiary is present in the country.[11] We then limit the sample to remove singletons - MNEs which only show up within a single reforming country and which would be dropped in fixed effects analyses regardless. In doing so, we identify 9,179 MNE assignees with 25,818 subsidiaries across the reforming countries, where a 'subsidiary' is defined as the pairing of a patent assignee and a country.

Outcome Measures Our primary outcome measure is the count of total patents for which an MNE subsidiary had any recorded involvement in producing, either through assignment or inventor participation as identified via the geo-location exercise. As our focus is on how global patenting activity shifts following such reforms, we focus on subsidiary production of two core patent types: (1) Global Collaborative Patents (GCPs)[12], classified as a patent with a geographic footprint inclusive of two or more countries, and (2) Domestic patents (DOMs), classified as patents localized within a country. We aggregate these measures to the MNE subsidiary-year level (defined by MNE f in country c at year t):

- **Total Patent Counts (pat_{fct}):** The sum of eventually-successful USPTO patent applications applied for in year $t+1$ by the MNE that are geo-located to the MNE subsidiary either through assignment or invention.

- **Global Collaborative Patent Counts (gcp_{fct}):** As above, but only for patents with a geographic

and country, whereas assignees –typically multinational firm offices– are listed at a specific address. Using these patent geo-locations, we identify for each standardized assignee organization all countries where patenting activity occurred belonging to the same standardized assignee across the globe and over time. In the event that an assignee exhibits patenting activity in multiple locations at any point, we assume that the assignee represents an MNE.

[11]The 2000 to 2014 limit reflects the years for which reforms are indexed for the study, even though we only consider the implications of reforms through 2013 due to forward censoring in patent measures.

[12]The global collaborative patent is first described in Kerr and Kerr (2018), and we draw on that paper as our motivation for using GCPs to measure globalized innovation processes. While defined in that study as an MNE patent with a U.S. and an international invention team, we define a GCP as any patent with a geographic footprint crossing an international border.

footprint that crosses international boundaries.

- **Domestic Patent Counts (dom_{fct}):** As above, but only for patents produced and assigned within one country.

We additionally consider whether reforms drive increases in patents produced by moving migrant inventors, the hypothesized mechanism through which the reforms function. Leveraging the USPTO's PatentsView dataset, we identify all patents within the UCB Fung data that are associated with migrant inventors. The PatentsView data provides a match of patents to disambiguated inventor portfolios and consequently allows for tracking of inventors and their locations over time. By tracking the change in the reported countries of inventors within the PatentsView data, we can identify permanent migrations of inventors over time as long as the inventors patent before and after their migration. Using the USPTO PatentsView data, we tabulate patent counts as above for all inventors who migrate to countries of interest:

- **Migrant patent counts, 1 year ($mig1yr_{fct,type}$):** As above, but for all patents applied for within one year of an inventor's identified migration. This is the baseline measure for migration analyses.
- **Migrant patent counts, Always ($migAlw_{fct,type}$):** As above, but for all patents applied for at any point after an inventor's identified migration.

Reform Exposure Measures We additionally use patenting activity to estimate the exposure of the MNE subsidiaries to the enacted reforms. Conceptually, reforms impact the MNE's globalized invention through shifting the ease of collaborations within the MNEs network - after a reform, it is less difficult to conduct in-person collaborations via migration. As a result, we posit that MNE subsidiaries exposure to the effects of reforms depends on the scope of the MNE innovation network external to the subsidiary. For example, following a positive reform to business travel, subsidiaries with a more expansive MNE network involving more numerous innovation-active sister-affiliates are likely more capable of taking advantage of the reform than are subsidiaries with a smaller spread of invention and fewer innovation-active MNE network affiliates. We therefore compute for each subsidiary measures of exposure based on the extent of innovation-active sister affiliates. Specifically, we measure:

- **Reform Exposure (exp_{fct}):** The number of unique sister affiliates (other countries where the MNE patents) in the five years prior to the reform.

Table 2.2: Subsidiary and Patent Counts Across Reforming Countries

	Number of Patents			Number of MNE
Country	Total Pat.	GCPs	Domestic	Subsidiaries
Brazil	2,380	1,856	524	524
Canada	48,391	32,612	15,779	2,943
Chile	230	184	46	107
China	55,132	42,789	12,343	2,929
Germany	151,461	68,202	83,259	4,441
India	20,365	17,976	2,389	1,1175
Italy	20,314	12,451	7,863	1,910
Japan	523,101	53,256	469,845	2,835
Mexico	1,337	1,239	98	343
Philippines	600	588	12	125
Portugal	485	437	48	228
South Korea	137,291	13,475	123,816	1,205
Spain	5,671	4,525	1,146	1,095
Taiwan	100,031	33,306	66,725	1,749
United Kingdom	56,898	43,954	12,944	4,209

Notes: This table displays the total patent and MNE subsidiary counts by country for the years 2000 - 2013 and for the MNE subsidiaries examined in the panel.

Table 2.2 displays the frequency of subsidiaries and patents of the different types across the reform countries during the years of the sample. There is substantial heterogeneity among the presence of MNE subsidiaries across the countries, with European / Western (e.g. Canada, Germany, the United Kingdom, etc.) followed by Asian (e.g. Japan, China, etc.) countries having the largest frequency of MNEs in residence. Additionally of note, certain countries produce global collaborative patents at greater rates than domestic patents and at significantly higher rates than those found in Kerr and Kerr (2018), who measure collaborative patenting rates among U.S. MNEs of between approximately 30% and 55%, where we measure GCP rate in excess of 50% of a country's total for several of the countries examined. This is likely due to across-country variation and also due to slightly more inclusive definition - the current study allows for identification of global collaborative patents based on geo-located ties crossing any international border and inclusive of assignee-ties.[13]

[13] Of the just over 4 million patents matched to the sets of assignees identified as MNEs in the data, roughly 12% (629,437) are identified as GCPs whereas when the definition is restricted to only those with global inventor teams, approximately 5% (251,743) are identified as GCPs.

Final sample

When the reforms are combined with the patent measures, the data consist of a finalized panel at the MNE-country-year level that is balanced within country and which consists of 361,452 observations indexing 9,179 MNE with a total 25,818 subsidiaries across the 13 years observed. Descriptive statistics for various levels of the data and the panel are presented in Table 2.3. A couple observations are of note. First, global collaborative patenting and patenting by migrants represent the minority of patenting. Global collaborative patents represent, on average, approximately 29% of patent production by MNE subsidiaries in the reform countries. Similarly, the statistics suggest that migrant inventor patents, when measured based on observed permanent migration, represent a relatively small portion of MNE patenting activity. In a given application year, the average country in the sample produces (at least in-part) only 276 MNE patents attributable to inventors who migrated within one year of the application while also contemporaneously producing almost six thousand total patents.

Second, the scope and scale of innovation are both highly skewed among the MNEs within the sample, as is characteristic of innovation contexts. Among the MNEs within the sample, a given MNE has on average 0.64 subsidiaries that are observed to apply for a patent in a given year across the 15 researched countries based on observed patenting, while MNEs in the distribution tail achieve patenting across up to 13 subsidiaries in a given year. Similarly, MNE subsidiaries have only 2.02 innovation-active sister affiliates on average in a given year across the MNE's full network of affiliates, but in the tail, this is as high as 51 sister affiliates with recent patenting activity based on the exposure measure.

Table 2.4 displays the correlation among key variables and provides additional insight into their interrelationship. Of note, the exposure measure (i.e. the index counting recently active sister affiliates, a measure of MNE network scope) correlates strongly with the overall volume of MNE patenting activity (e.g. a measure of MNE scale). Reforms additionally weakly correlate with observed patenting.

2.2.2 Empirical Strategy

Our empirical strategy relies on applying an event study framework in which identification relies on the assumption that migration policy reforms – our "treatment" events – are exogenous to the MNE subsidiaries within the enacting country. To ensure exogeneity, we exploit that, although assignment of reform events

Table 2.3: Descriptive Statistics, 2000 to 2013

Variable	Mean	Std. Dev.	Min	Q1	Q2	Q3	Max
	Country-Year ($N = 15$ Countries Researched)						
All Patents							
Num. GCPs	1,467	1,701.40	0	58	698	2,865	6,244
Num. Domestic	3,641	8,569.52	0	5	207	2,176	38,941
Migrant Patents - 1 year							
Num. GCP	119	193.48	0	3	33	163	1,111
Num. Domestic	157	260.43	0	0	12	255	1,153
GDP (Billions)	1,501	1,624.65	0	278	1,070	2,038	9,607
Total Population (Millions)	210	393.63	0	23	59	123	1,357
	MNE-Year ($N = 9,179$ MNEs)						
All Patents							
Num. GCPs	2.57	25.10	0.00	0.00	0.00	1.00	2,654
Num. Domestic	6.38	72.42.60	0.00	0.00	0.00	0.00	5,186
Migrant Patents - 1 year							
Num. GCPs	0.21	2.94	0.00	0.00	0.00	0.00	307
Num. Domestic	0.28	4.60	0.00	0.00	0.00	0.00	494
Num. Subsidiaries	0.64	1.10	0.00	0.00	0.00	1	13
Num. Inventors	21.39	214.84	0.00	0.00	0.00	3.00	16,392
	Final Panel, MNE Subsidiary-Year ($N = 361,452$)						
All Patents							
Num. Patents	3.11	47.34	0.00	0.00	0.00	0.00	5,686
Num. GCPs	0.90	10.04	0.00	0.00	0.00	0.00	1,364
Num. Domestic	2.20	42.64	0.00	0.00	0.00	0.00	5,186
Migrant Patents - 1 year							
Num. Patents	0.17	3.27	0.00	0.00	0.00	0.00	539
Num. GCPs	0.08	1.32	0.00	0.00	0.00	0.00	259
Num. Domestic	0.10	2.79	0.00	0.00	0.00	0.00	494
Num. Inventors	7.65	125.66	0.00	0.00	0.00	0.00	16,180
Exposure Measures							
Num. Sister Affiliates	2.02	3.51	0.00	0.00	1.00	2.00	51
exp_{fct}	3.74	5.69	0	0	2	5	60
$lag_{t-15}(exp_{fct})$	0.92	2.61	0	0	0	1	47

Notes: The table presents summary statistics of the data at different levels as well as for the final panel consisting of MNE subsidiary observations (at the assignee-country level) matched to data on reforms to migration policy and global collaborative patenting data. Number of Inventors refers to the number of inventors observed patenting in that year as uniquely identified by first and last name within a subsidiary.

Table 2.4: Correlation Among Key Measures in Panel

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) Num. Patents (pat_{fct})	1.00										
(2) Num. Mig. Pats. ($mig1yr_{fct,pat}$)	0.746	1.000									
(3) Num. GCPs (gcp_{fct})	0.551	0.585	1.000								
(4) Num. Mig. GCPs ($mig1yr_{fct,gcp}$)	0.246	0.538	0.703	1.000							
(5) Num. Domestic (dom_{fct}	0.980	0.690	0.376	0.108	1.000						
(6) Num. Mig. Dom. ($mig1yr_{fct,pat}$)	0.757	0.916	0.351	0.155	0.757	1.000					
(7) Reform Indicator ($\mathbb{1}(reform_{ct})$)	0.006	0.002	0.001	-0.003	0.006	0.003	1.000				
(8) Cumulative Reform Count (r_{ct})	-0.005	0.005	0.000	0.007	-0.005	0.002	0.423	1.000			
(9) Exposure (exp_{fct})	0.089	0.090	0.159	0.117	0.061	0.050	0.009	0.047	1.000		
(10) 15-Year Lagged Exposure ($lag_{t-15}(exp_{fct})$)	0.051	0.046	0.091	0.067	0.036	0.022	0.009	0.058	0.618	1.000	
(11) Total MNE Patents (1976 - 2014)	0.226	0.183	0.244	0.179	0.193	0.129	-0.001	-0.006	0.553	0.511	1.00

Notes: The table shows the correlation among key measures in the panel. $lag_{t-15}(exp_{fct})$ is the 15-year lag of the exposure measure exp_{fct}.

is potentially endogenous to country-level characteristics and trends, subsidiaries within the same country vary in the extent to which they are capable of taking advantage of reforms in their innovation activities.[14] How? Based on the ex-ante location of their sister affiliates.

For instance, subsidiaries in a reform country with many invention-active sister affiliates across many countries, as opposed to few invention-active sister affiliates across few countries, should exhibit greater propensity to collaborate broadly via cross-border coordination on inventions following the implementation of positive reforms. Accordingly, subsidiary innovation can be thought of as a function of reforms to migration policy as well as the scope of the contemporaneous MNE network (i.e., 'exposure'). We model this as:

$$Y_{fct} = f(\alpha_{ft} + \alpha_{ct} + \beta_1 \ exp_{fct} + \beta_2 \ r_{ct} \times exp_{fct}; \ \epsilon_{fct}) \tag{2.1}$$

where Y_{fct} represents the innovation outputs in year t of an MNE subsidiary defined as the combination of an MNE firm f and a country location c. The outputs are a function of: (1) exp_{fct}, the scope of the subsidiary's MNE innovation network and (2) r_{ct}, a count variable indexing the number of reforms enacted by year t in the subsidiary country c. The key term of interest is the interaction $r_{ct} \times exp_{fct}$, which indexes cumulative reform events scaled by the extent of each subsidiary's exposure to the reform. The outputs are additionally conditioned on a standard error term (ϵ_{fct}), as well as fixed effects at the levels of MNE-year (α_{ft}) and country-year (α_{ct}), in order to identify the effects of reforms independent of MNE and country trends.

[14] Thus, our identification strategy cannot rely only on comparing countries with and without reforms before and after, given that governments may enact reforms in anticipation of shifting innovation trends inducing reverse causality.

The counterfactual modeled by this approach is to compare the change in innovation output of high exposure subsidiaries before and after reform events with the change among low exposure subsidiaries, while netting out changes attributable to the country and the firm over time. Low exposure subsidiaries serve as a control group for treated subsidiaries, and we argue that exposure is exogenous to the reform itself. We additionally include in estimation MNE subsidiaries in untreated countries. Although the MNE subsidiaries provide no power to estimation of the treatment effects itself as the counterfactual comparison is within country, they allow for more robust estimation of MNE fixed effects as well as the impacts of subsidiary exposure to the MNE network.

Corresponding analyses use high-dimensional fixed effects (HDFE) statistical programming packages, as the number of fixed effects (9,179 x 13 for MNEs alone) exceeds the computational limits of non-HDFE regression approaches. Our primary specifications fit Equation 2.1 with arcisnh transformed outcomes via the HDFE Stata package (Correia, 2016) as our measures of innovation are sparse counts. In robustness checks we present HDFE Poisson regression as a robustness check (see Appendix B.4).

Interpreting Treatment Effects Given Repeated, Clustered Reform Events

An estimation challenge in this setting is the presence of repeated events which are highly clustered in time. Standard econometric practice suggests isolating to those observations only 'treated' once or estimating treatment effects only in short-run windows without repeat treatment immediately following events. However, neither technique is well-suited to the current setting. As reform events are enacted repeatedly within five countries (Germany, Japan, Mexico, South Korea, and Spain), omitting multiply treated observations would reduce the data by approximately 38% (see Table 2.2). Reforms events are additionally clustered in time, which severely limits the sample of periods for which it is possible to estimate short-run treatment effects independent of other reform events (see Table 2.1).

To resolve this difficulty, we introduce a novel empirical approach to estimating treatment effects given repeated and clustered-over-time treatments. We do so through structuring regressions to estimate the marginal treatment effects of each consecutive reform event. Specifically, we allow the event indicator term (r_{ct}) to dynamically vary, changing in level as treatment events accumulate over time.[15] In a linear

[15]This term is akin to employing an 'intensity of treatment' variable in difference-in-differences, in which treatment obtains multiple levels or reflects an observation's propensity to treatment (similar to specifications employed in, e.g.,

regression, the key coefficient β_2 is interpreted as the marginal effect per-year of an additional reform on innovation outputs.[16] Appendix B.3 reports simulations that validate the estimator, discusses the additional assumptions it imposes on causal inference, and outlines a generalized version of the estimator that allows treatment effect to vary conditional on the level of consecutive events.

2.3 Results

Do MNEs take advantage of pro-business migration policy reforms? Our results suggest that they do, with total patent, GCP, and DOM production increasing by 11%, 22.5%, and 7% among the average MNE. We find that the reforms drive increases in patenting among 'long-term' migrant inventors and also among other inventors, and that larger MNEs are more able to take advantage of pro-business migration reforms. We present below the baseline results on the estimated marginal treatment effect of reforms and the estimated dynamic treatment effects of the reforms in event time. As our measure of exposure is correlated with the size of the MNE, and as MNEs exhibit a long-tail distribution in measures of size (proxied for via innovation volume), we then show that the impacts of reforms on patent production are driven by MNEs above mean size. We also show that the increases in patenting occur primarily among non-permanent migrant inventors.

2.3.1 Treatment Effects of Reforms

Impacts on All MNE Patenting

We first fit variations of Equation 2.1 on the one-year lead measures of the dependent variables and display the results in Table 2.5. Columns (1) to (3) display the results for the one-year forward lead measures of the overall number of patent counts, GCP counts, and domestic patent counts while columns (4) to (6) show results for migrant inventor patents. The table additionally displays the average marginal effects for the sample retained within the regression (as the regressions include standard errors clustered at the level of

Duflo 2001; Acemoglu et al. 2004), but where the intensity of treatment varies with time.

[16] In linear regression and taking the unlogged annual MNE subsidiary GCP quantity as the dependent variable in Equation 2.1, enacting an additional reform on average increases the quantity of GCPs produced per year at affected MNE subsidiaries by $\beta_2 \cdot exp_{fct}$. The dependent variables leveraged in the study are typical of patent data - sparsely populated count measures with many zeros and a long-tail. We therefore arcsinh transform dependent variables. This changes the interpretation of β_2 such that its marginal effect is non-linear when condition on exp_{fct} and r_{ct}. With regards to r_{ct}, the estimates of β_2 are small enough that each additional reform exhibits roughly equivalent impact on the dependent variables. However, further interpretation requires analysis of margins.

Table 2.5: Patenting and Pro-Business Migration Reforms

	All MNE Patents			Migrant Inv. Patents		
Arcsinh Transformed:	(1) pat_{fct}	(2) gcp_{fct}	(3) dom_{fct}	(4) $mig1yr_{fct,pat}$	(5) $mig1yr_{fct,gcp}$	(6) $mig1yr_{fct,dom}$
Cumulative Reforms	0.0074***	0.0056***	0.0037***	0.0029**	0.0023*	0.0010+
$(r_{ct}) \times exp_{fct}$	(0.0017)	(0.0016)	(0.0011)	(0.0010)	(0.00089)	(0.00057)
exp_{fct}	-0.71***	-0.35***	-0.50***	-0.13***	-0.046***	-0.088***
	(0.014)	(0.0081)	(0.013)	(0.0050)	(0.0026)	(0.0044)
Constant	3.04***	1.56***	2.01***	0.53***	0.21***	0.36***
	(0.054)	(0.032)	(0.052)	(0.019)	(0.0098)	(0.017)
Avg. Marginal Effect of r_{ct}						
	[1.028]	[1.021]	[1.014]	[1.011]	[1.009]	[1.004]
AME in log diff.	0.0275***	0.0208***	0.0137***	0.0107**	0.0085*	0.0038+
	(0.0064)	(0.0059)	(0.0040)	(0.0038)	(0.0033)	(0.0021)
AME in Δ patents	0.0329***	0.0143***	0.0095***	0.0065**	0.0066*	0.0039+
	(0.0077)	(0.0041)	(0.0095)	(0.0023)	(0.0026)	(0.0014)
MNE X Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country X Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N. Obs	361,452	361,452	361,452	361,452	361,452	361,452
Adj. R Within	0.09	0.05	0.07	0.02	0.01	0.02

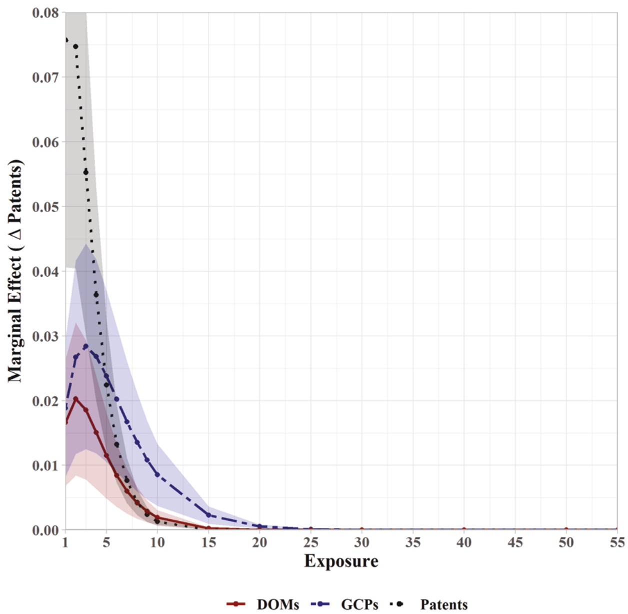
Notes: The table shows the results of high-dimensional fixed effects regressions of arcsinh transformed patent counts on exposure and cumulative reforms among the sample of retained observations (non-singletons). The first three columns show estimated coefficients for effects on total patents produced by MNE subsidiaries while the final three columns show the estimates for only migrant patents produced by MNE subsidiaries within one year of an inferred migrant move. The table additionally displays estimated average marginal effects based on the sample (mean exposure for observations retained in the regression sample is 3.745). Standard errors for estimates are clustered at the subsidiary (MNE-Country) level in parenthesis. Brackets display IRRs. Significance Levels: $+\ p < 0.10$, $*\ p < 0.05$, $**\ p < 0.01$, $***\ p < 0.001$.

the MNE-Country and several fixed effects dimensions, approximately half of observations are dropped due to insufficient variation).[17]

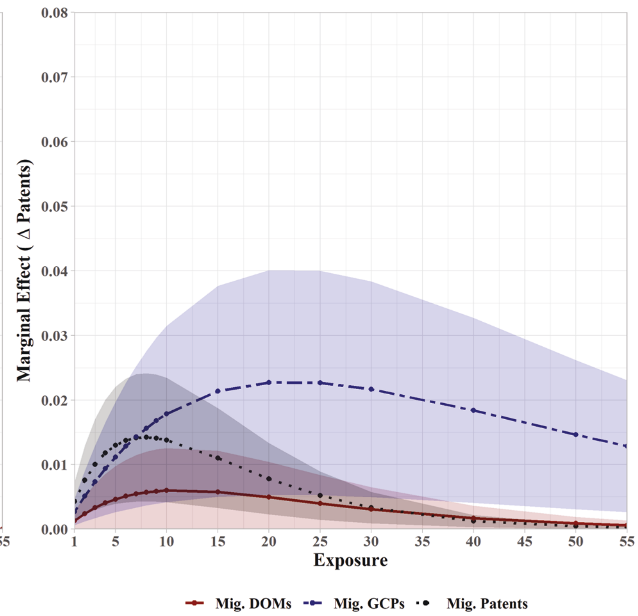
The results show that an additional enacted reform drives highly significant increases in MNE subsidiaries' subsequent per-year production of patents, GCPs, and domestic patents overall. At mean exposure, an additional reform increases subsidiaries' overall annual patent production by approximately 2.8% (0.041 additional patents), GCP production by 2.1% (0.027 additional global collaborative patents), and DOM production by 1.4% (0.016 additional domestic patents).[18] Relative to annual production in the unrestricted subsidiary sample, these increases represents approximate predicted growth in annual production of patents by 1.3%, GCPs by 3%, and domestic patents by 0.7% (see Table 2.3), indicating somewhat large increases

[17] See Correia (2015).

[18] At most, any country enacts two reforms during the sample period. For the MNE subsidiaries remaining in the regression, estimated marginal effects at means of implementing the first reform are to produce 0.04079 patents, 0.02745 GCPs, and 0.016025 additional DOMs when exposure is set to its mean. Implementing the second reform produces, on average, 0.041928 patents, 0.028029 GCPs, 0.016246 DOMs. Average marginal effects at means are 0.0407348 patents, 0.0274246 GCPs, and 0.0160145 DOMs. For the full sample, the implied effects of implementing the first reform is to increase total patents by 0.032, GCPs by 0.007, and DOMs by 0.011.



(a) All MNE Patenting



(b) Migrant Inv. Patents

Figure 2.1: Marginal Effects of Reforms on Patenting by Migrant Inventors

Notes: The figure displays the average marginal effect of an additional permanent pro-business reform in terms of Δ patenting outcomes, conditional on exposure. Shaded areas reflect 95% confidence intervals for point estimates.

in annual innovation, specifically via global collaborative patenting. Computing average marginal effects suggests that impacts across the distribution are somewhat smaller, with equivalent percent changes but predicted average marginal increases in patent counts of 0.014 GCPs, 0.010 DOMs, and 0.033 total patents for a given subsidiary. As the regression includes controls at the country-year and MNE-year level, these point estimates are independent of MNE scale as well as country-specific shocks over time that are unrelated to the reforms.

Marginal effects are instructive for understanding how patent production varies with the exposure measure. Figure 2.1a displays the estimated average marginal effects of an additional reform in terms of patents produced conditional on exposure. The results show that the estimated effects of reforms are greatest for those MNE subsidiaries with prior exposure to a somewhat expansive MNE affiliate network (e.g. between 2 and 5 subsidiaries), but that the returns to reforms diminish with the scope of the network, quickly disappearing for MNEs with many already established subsidiaries. Additionally, GCP production is most sensitive to an expansive MNE network - beyond five prior sister affiliates, GCPs exhibit greater marginal returns in terms of increases in annual patent applications than total patents or domestic patents.

Impacts on MNE Migrant Patenting

The remaining columns (4 to 6) of Table 2.5 indicate effects with respect to patents produced by migrant inventors. Positive effects significant at 95% level are identified for both migrant inventor patents (1.1% increase or 0.0065 patents) as well as migrant inventor global collaborative patents (0.9% increase or 0.0066 patents), and positive effects on the production of domestic patents are found to be weakly significant ($p<0.10\%$). When compared against means of the full sample, these changes represent 11%, 22.5%, and 7% increases respectively relative to subsidiary per year baselines.

Marginal effects in terms of the change in patents and conditioned on exposure level for migrant inventors are displayed in Figure 2.1b. As before, GCPs exhibit the greatest response at higher levels of exposure, peaking at around 20 to 25 sister affiliates, and with marginal returns remaining high relative to that of DOMs and all patents. Taken together, these results suggest that MNEs utilize reforms to increase patenting among impacted subsidiaries and that subsidiaries are differentiated in their response to reforms by the scope of the MNEs innovating affiliate network. Overall, MNEs with relatively low-scope networks (ranging from 1 to 5 innovating subsidiaries), benefit substantially from reforms in the form of further increases in patents, GCPs, and DOMs. By contrast, subsidiaries of greater scope (e.g. 20-25 innovating subsidiaries) are more prone to take advantage of their networks through permanent relocation of inventors who then produce global collaborative patents that likely span the MNE network.

2.3.2 Robustness

This section evaluates the robustness of these core findings. First, we consider reduced form specifications of Equation 2.1 wherein the contemporaneous exposure of MNE subsidiaries is proxied for by the 15-year lagged historical exposure of the MNE subsidiary - a measure that is almost-surely exogenous to MNEs' reform-contemporaneous staffing decisions. Second, evidence is presented of the dynamic treatment effects of the reforms in an event-time framework. Together, the results illustrate robust and immediate returns to the MNE subsidiaries in the form of increased production of global collaborative patents and total patents overall as well as those patents produced by migrating inventors.

For additional robustness checks, see Appendix B.4. The appendix includes results of (1) fitting Equation 2.1 via Poisson fixed effects regressions more aptly suited to count data, and (2) regressions involving variations of the exposure measure.

Proxying Contemporaneous Exposure Via Historical Exposure

The main threat to causal inference of this estimation approach is that subsidiary exposure to the MNE network contemporaneous to reforms may be jointly determined with current and future innovative activity. As policy reforms are often debated, reported on, and announced in-advance of implementation, subsidiaries may anticipate reform events and adjust their staffing and resource strategies well in advance of reform implementation. Likewise, MNEs may influence the enactment of reforms conditional on anticipated innovation trends prior to the reforms.

However, anticipation of reforms depends on proximity in time. The exact allocation of the MNE's innovation network and the subsidiary's contemporaneous exposure to the network is likely increasingly endogenous to the reform events the closer in time exposure is measured relative to the reform occurrence.[19] Variation in the long-run historical R&D investments of MNEs almost certainly affects the extent to which MNEs are exposed to reforms, but also is exogenous to MNEs' short-run resource allocation decisions which may be driven by reform anticipation. To estimate an unbiased causal effect, we therefore proxy for the contemporaneous exposure of subsidiaries with their historical exposure by estimating the following reduced form:

$$Y_{fct} = f(\alpha_{ft} + \alpha_{ct} + \beta_1\ lag_{t-15}(exp_{fct}) + \beta_2\ r_{ct} + \beta_3\ r_{ct} \times lag_{t-15}(exp_{fct}) + \epsilon_{fct}) \tag{2.2}$$

where $lag_{t-15}(exp_{fct})$ is the exposure measure in year $t-15$.

Table 2.6 presents the results. For the estimated impacts on all MNE patents, the results are generally consistent with the simple OLS specifications for GCPs, while lesser in magnitude (the average marginal increase and marginal effect at means in GCPs is estimated at roughly 0.5%, or approximately 0.0017 patents, which is roughly a 0.3% increase in annual GCP production). On the other hand, the reduced form estimation

[19] MNEs are likely constrained to some extent in their R&D resource allocations based on their historical long-run investments. On short notice, to some extent, employees may migrate in or out of countries and local physical assets such as plant, property, and equipment may be liquidated or purchased in response to anticipated changes in migration policy. However, other complementary assets can only be developed with long-run investment and are difficult to re-allocate in the short-run. Complementary assets, such as localized MNE manufacturing activities or local technical expertise, talent clustering, and access to local networks exhibit 'stickiness' in that they are both difficult to replace or substitute for in the short-run and confined to the local geography - the countries enacting the reforms.

fails to identify an effect of reforms on the production of patents overall or DOMs specifically, although the direction of both estimates remains positive. For MNEs' migrant inventor patents, reforms are identified to exhibit weakly significant (at the 90% significance level) positive impacts on the forward production of GCPs (producing about 0.3% more patents, or 0.0017 migrant GCPs, when considering average marginal effects), while insignificant but positive impacts are identified on total and domestic patenting.

These results indicate reforms primarily drive causal increases in patenting via the creation of new GCPs among impacted MNE subsidiaries, and suggests that the full GCP change may be accounted for by GCPs produced by new migrants. Results with varying significance levels but similar effect magnitudes are identified in Poisson regressions as well as regressions involving an alternatively specified exposure variable and can be found in Appendix B.4.

Table 2.6: Historical Exposure 'Reduced Form'

	All MNE Patents			Migrant Inv. Patents		
Arcsinh Transformed:	(1)	(2)	(3)	(4)	(5)	(6)
	pat_{fct}	gcp_{fct}	dom_{fct}	$mig1yr_{fct,pat}$	$mig1yr_{fct,gcp}$	$mig1yr_{fct,dom}$
Cumulative Reforms	0.0044	0.0055*	-0.00084	0.0024	0.0027+	0.00021
$(r_{ct}) \times lag_{t-15}(exp_{fct})$	(0.0028)	(0.0025)	(0.0022)	(0.0017)	(0.0014)	(0.0010)
$lag_{t-15}(exp_{fct})$	-1.13***	-0.48***	-0.96***	-0.25***	-0.074***	-0.21***
	(0.040)	(0.024)	(0.041)	(0.018)	(0.0087)	(0.017)
Constant	1.43***	0.71***	1.04***	0.29***	0.10***	0.22***
	(0.038)	(0.023)	(0.040)	(0.017)	(0.0083)	(0.016)
Avg. Marginal Effect of r_{ct}						
	[1.004]	[1.005]	[0.999]	[1.002]	[1.003]	[1.000]
AME	0.0040	0.0050*	-0.0008	0.0022	0.0025+	0.0002
	(0.0025)	(0.0023)	(0.0020)	(0.0016)	(0.0013)	(0.0010)
AME in Δ patents	0.0009	0.0017*	-0.0002	0.0009	0.0017+	0.0001
	(0.0006)	(0.0008)	(0.0004)	(0.0006)	(0.0009)	(0.0004)
MNE X Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country X Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N. Obs	361,452	361,452	361,452	361,452	361,452	361,452
Adj. R Within	0.09	0.03	0.09	0.03	0.01	0.03

Notes: The table shows the results of high-dimensional fixed effects regressions of arcsinh transformed patent counts on 'historical' (15-year lagged) exposure and cumulative reforms among the sample of retained observations (non-singletons). The first three columns show estimated coefficients for effects on total patents produced by MNE subsidiaries while the final three columns show the estimates for only migrant patents produced by MNE subsidiaries within one year of an inferred migrant move. The table additionally displays estimated average marginal effects based on the sample (mean exposure for observations retained in the regression sample is 0.9184622). Standard errors for estimates are clustered at the subsidiary (MNE-Country) level in parenthesis. Brackets display IRRs. Significance Levels: $+\ p < 0.10$, $*\ p < 0.05$, $**\ p < 0.01$, $***\ p < 0.001$.

Dynamic Treatment Effects and Parallel Trend

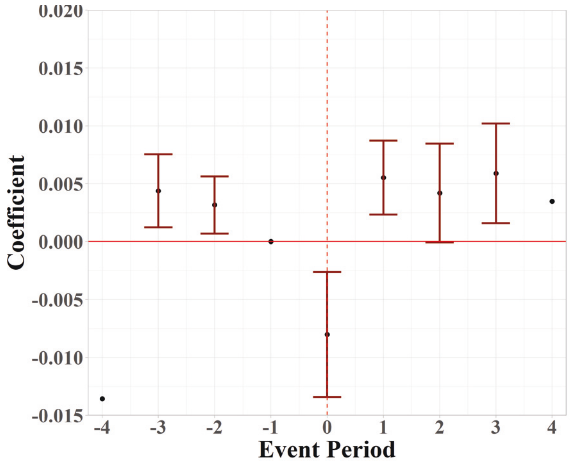
As a second robustness check, we consider dynamic effects in event-time and evaluate whether subsidiaries treated to reform events exhibit parallel trends to untreated subsidiaries in advance of reforms. As migration reforms are repeat events, the presence of pre-trend differences between treated and untreated observations may reflect the presence of a prior, valid treatment effect, and so we estimate for parallel pre-trends in the short-run. We model dynamic treatment effects as:

$$Y_{fct} = f(\alpha_{ft} + \alpha_{ct} + exp_{fct} + \sum_{k=\underline{C}}^{\overline{C}} \delta_k \mathbb{1}(R_{ct}^k \times exp_{fct}) + \epsilon_{fct}) \tag{2.3}$$

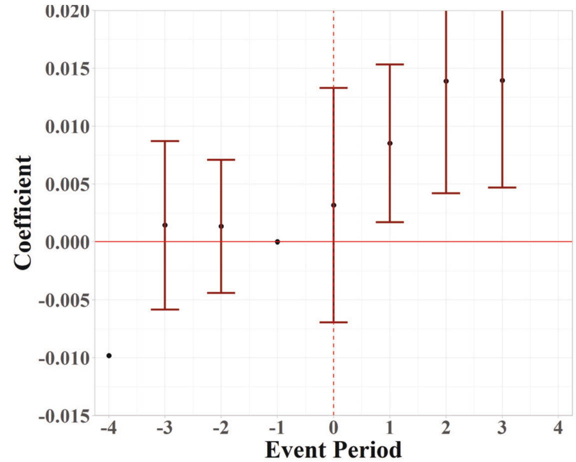
where k indexes event time relative to the nearest reform, $\mathbb{1}(R_{ct}^k)$ is a series of indicator variable indexing observations k periods after a reform event, and $\underline{C}$ to $\overline{C}$ indicate two 'cutoff' points that index periods at or prior to a certain event time ($\underline{C}$) or periods at or after a certain event time ($\overline{C}$).[20] Here, δ_k identifies the dynamic marginal treatment effect of reforms at event-time k relative to an omitted baseline period (the year prior to reform enactment). This estimate can be thought of as a by-year estimate of the β_2 coefficients in Equation 2.1 that comes at the expense of omitting information on reform events' links to all but the most proximate years.

Figure 2.2 plots the point estimates and corresponding 95% confidence intervals of δ_k in event-time for both the simple OLS and reduced form regressions where the dependent variable set is that of all patents produced by MNEs. The figure shows that in simple regressions leveraging the contemporaneous exposure measure (left column), significant pre-trend violations exist with respect to the impacts on both patent (Subfigure 2.3a) and GCP (Subfigure 2.3c) production. However, the reduced form results (right column), which leverage the lagged 'historic' exposure measure, show only very slight violations of parallel pre-trend assumptions while exhibiting distinct upward ticks after reform events in both overall patenting and global collaborative patenting that are significant at the 95% level (i.e. increases of roughly 0.7% to 5% in annual GCP production and 1.5% to 4% in total patents in the three years after the implementation of an additional

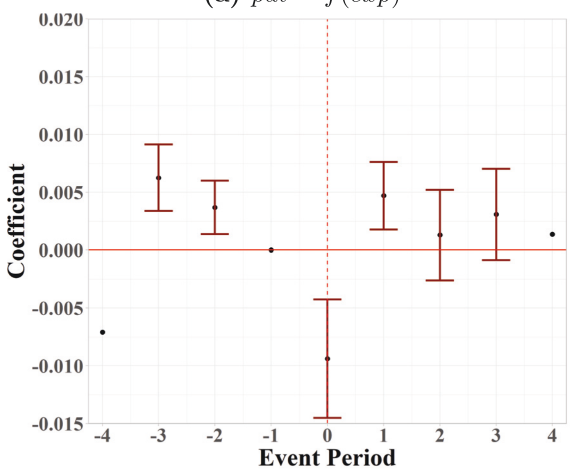
[20] Determining relative event time is complicated given repetition within-countries of reforms. If event-time indicators are coded such that they reflect all event times for multiple reforms, the regression is over-identified. We therefore take the imperfect but useful step of coding R_{ct}^k to give preference to times of relative lesser magnitude with ties assigned to forward event time. Spain, for example, enacts reforms in 2003 and 2009, and observations for MNE subsidiaries located there in year 2006 are assigned $\mathbb{1}(R_{ct}^3) = 1$ and $\mathbb{1}(R_{ct}^{-3}) = 0$. To maintain a relatively balanced panel, cutoffs $\underline{C}$ and $\overline{C}$ are set at four years prior and four years after reform events.



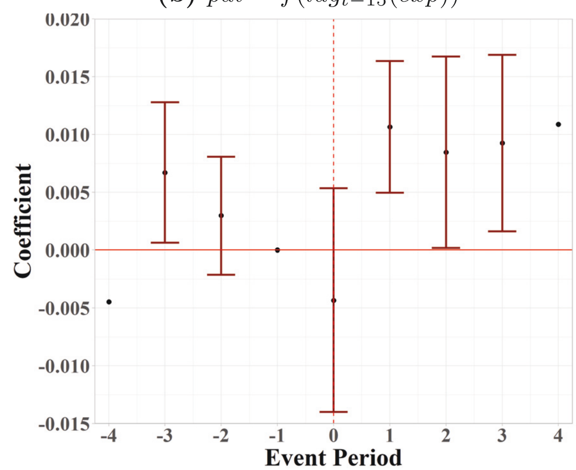
(a) $pat = f(exp)$



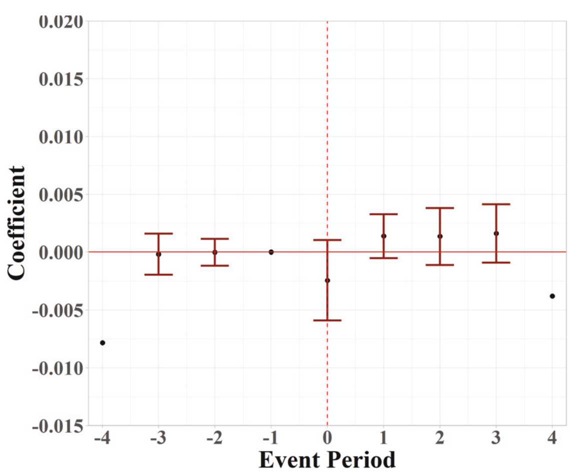
(b) $pat = f(lag_{t-15}(exp))$



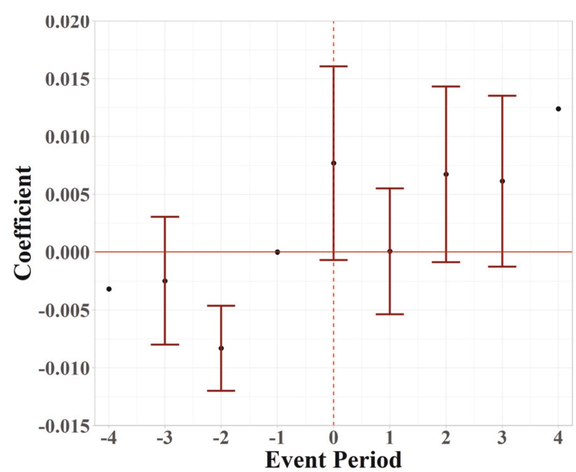
(c) $gcp = f(exp)$



(d) $gcp = f(lag_{t-15}(exp))$



(e) $dom = f(exp)$



(f) $dom = f(lag_{t-15}(exp))$

Figure 2.2: Dynamic Treatment Effects of Reforms on All MNE Patents

Notes: The figure displays the coefficients and confidence intervals of $r_{ct} \times exp_{fct}$ in regressions of all MNE patents. The left column displays simple OLS regression with contemporaneous exposure, while the right column displays reduced form results with historic exposure. The first row corresponds to total patents, the second row GCPs, and the third row DOMs. Whiskers reflect 95% confidence intervals for point estimates. Cutoff coefficients are represented without confidence intervals.

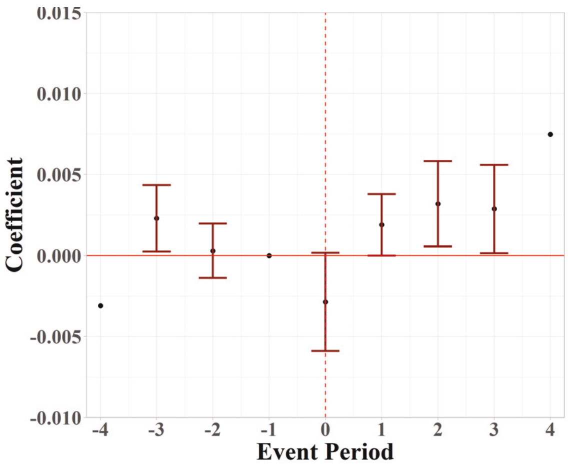
reform event among a subsidiary of mean exposure and depending on specification considered). Domestic patents, by contrast, provide little reason to trust that the true estimated effects of reforms are anything but imprecise zeros - in the simple OLS specification domestic patents exhibit no significant change in the periods around reforms, and the results in the reduced form specification only show significant deviations in the form of a violation of parallel trend.

Results for migrant patent counts are displayed in Figure 2.3. Here, the event specification provides greater evidence of a robust effect of business reforms on total migrant patents produced *vis-a-vis* increasing migrant GCP production, although these effects are smaller than those of the overall counts. Depending on specification and period considered, overall patent production within subsidiaries by migrants is estimated to increase by roughly 0.8% to 3.2% and GCPs by 1.1% to 2.6% in periods subsequent to reform events for subsidiaries of mean exposure. Further, parallel trend deviations are non-existent for either migrant GCP specification, and only marginally identifiable for the OLS patent specification. Domestic migrant patents, while lacking parallel trends, exhibit no significant increases immediately subsequent to reform events.

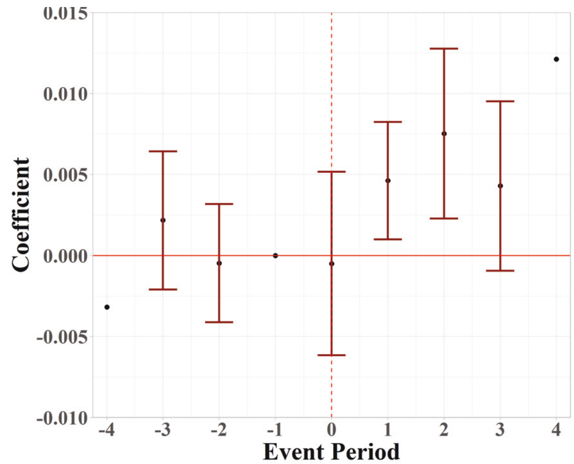
In both figures, cutoff indicators are estimated in the regression, with their confidence intervals omitted from display; however, the results prove robust to omitting cutoff indicators (see Appendix B.4).

2.3.3 Results on Mechanisms

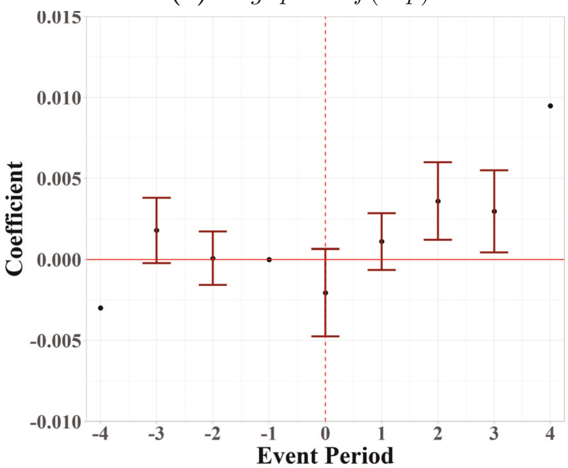
Although reforms generate a robust, positive effect on subsequent overall patenting and GCP patenting, questions remain regarding the mechanisms through which additional patents are produced. We consider two mechanisms that may drive the production of patents: MNE size and migrant inventors. For the former, scale of within-business operations is often hypothesized to directly relate to the capability to manage cross-border production and knowledge activities (e.g. Caves 1971), and we have already seen that MNE invention scope (e.g. exposure) is highly correlated with the scale of MNE invention activities (e.g. total patent volume). We therefore evaluate heterogenous treatment effects by MNE size and find that the returns to patenting due to policy reforms are indeed driven by MNEs of above mean size. For the latter, an open question remains as to whether long-term migrants' patenting account for the majority of increases in patents following reforms, or whether patenting is driven by short-term and cyclical migration and/or spillovers. We investigate this question in the second part of this section.



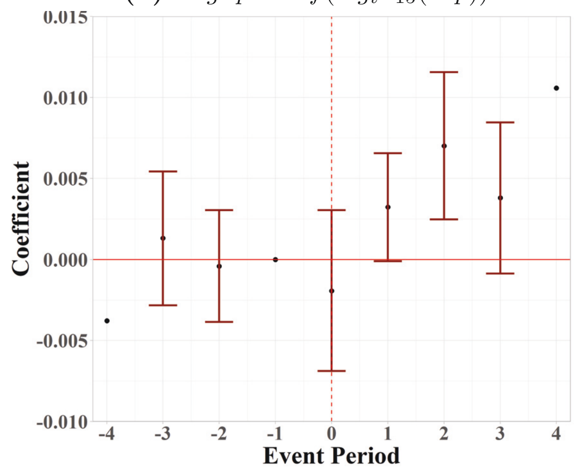
(a) $mig.\ pat = f(exp)$



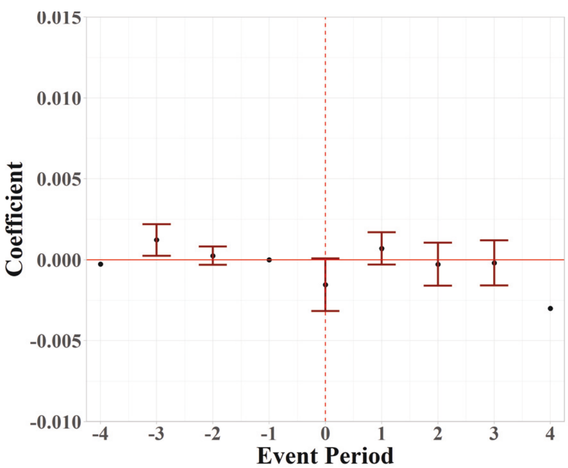
(b) $mig.\ pat = f(lag_{t-15}(exp))$



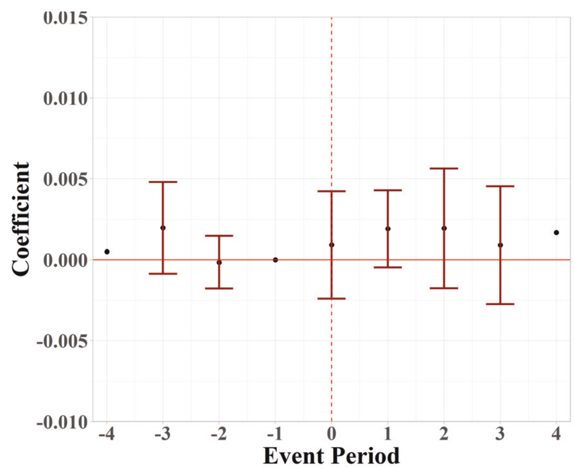
(c) $mig.\ gcp = f(exp)$



(d) $mig.\ gcp = f(lag_{t-15}(exp))$



(e) $mig.\ dom = f(exp)$



(f) $mig.\ dom = f(lag_{t-15}(exp))$

Figure 2.3: Dynamic Treatment Effects of Reforms on MNE Migrant Patents

Notes: The figure displays the coefficients and confidence intervals of $r_{ct} \times exp_{fct}$ in regressions of MNE migrant patents. The left column displays simple OLS regression with contemporaneous exposure, while the right column displays reduced form results with historic exposure. The first row corresponds to total patents, the second row GCPs, and the third row DOMs. Whiskers reflect 95% confidence intervals for point estimates. Cutoff coefficients are represented without confidence intervals.

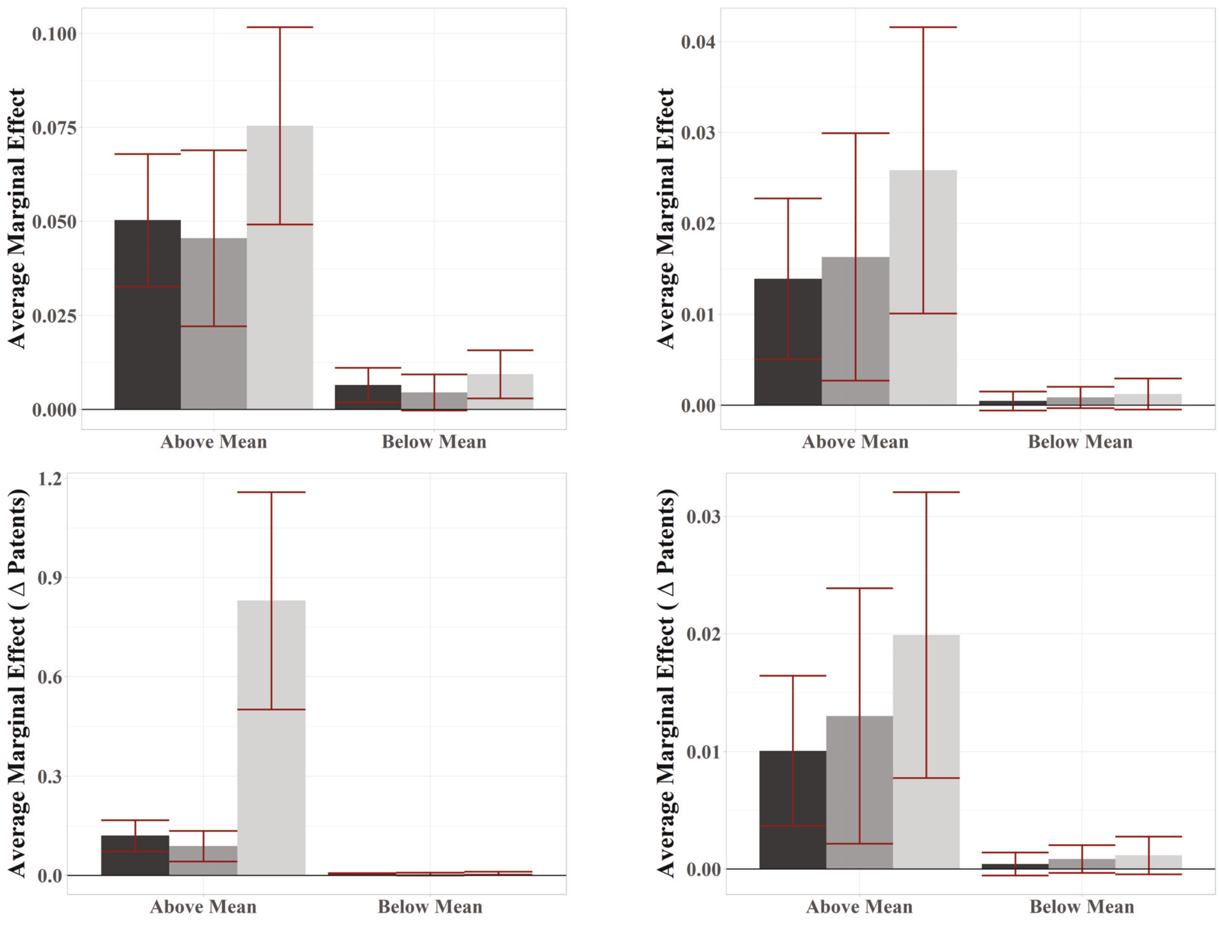
Heterogeneous Treatment Effects by MNE Size

To investigate whether treatment effects vary as a function of MNE size, we refit Equation 2.1 leveraging two samples of the data: (1) MNEs with above mean total patent volume across all patents produced globally, and (2) MNEs with below mean total patent volume. From these estimates, we then computed the average marginal effects, in terms of both the estimated log difference (i.e. equivalent to the standard coefficient) as well as the estimated difference in patents produced. Figure 2.4 displays the results of these computations alongside 95% confidence intervals with the effects for DOMs in black, GCPs in dark grey, and overall patenting in light grey.

The results in the figures illustrate that effects are indeed conditional on the scale of the MNE, with the bulk of increases driven by MNEs of above-mean size (i.e. above mean total patent volume). In terms of percent returns among all patents produced by the subsidiary (subfigure column a), the average marginal effect is several orders of magnitude larger for above-mean MNEs, with point estimates of percent increases in patenting conditional on mean exposure ranging from roughly 4.5% (for GCPs) to 7.5% (for overall patent counts). When translated into patent counts, the estimated average marginal effects of an increase in the number of reforms enacted are to increase annual subsidiary production of GCPs by between 0.04 and 0.13 units, of DOMs by between 0.07 and 0.16 units, and total patents by between 0.5 and 1.15 units. All effects are distinguishable from those for the below mean subset at $p < 0.05$.

Similar results are obtained when considering patents by migrant inventors (subfigure column b), with three notes. First, point estimates for log differences are smaller but similar in the counts of patents produced. Second, unlike the sample of all patents, estimated GCP production of migrant patents is larger than that of domestic patent production, suggesting migrant inventors are more likely to produce global patents than the average inventor. Finally, confidence intervals are substantially wider, with the effects on migrant GCPs counts no longer distinguishable at $p < 0.05$, although the effects are distinguishable at $p < 0.10$.

One concern of this approach may be that by segmenting the sample of MNEs by total patent volume means over the full time of the patent data (1976 - 2014), we are incorrectly segmenting MNEs as scale of invention may vary substantial over time. Additional results in Appendix B.4 investigate this analysis while allowing size to vary with time, and find that the point estimates of effects are robust and the rough magnitude of difference between large and small MNEs remains, although the differences are not consistently



(a) All Patents

(b) Migrant Inv. Patents

Figure 2.4: Average Marginal Effects of Reforms by MNE Size

Notes: The figure displays the difference in average marginal effects (in patents produced) between MNE subsidiaries with above and below mean size (proxied by total patent volume during 1976 - 2014) based on segmented regressions of Equation 2.1 (N. Obs 'Above Mean' = 163,324; N. Obs 'Below Mean' = 198,128). Dark grey bars correspond to predicted change in DOMs, medium grey bars to GCPs, and light grey bars to total patents. Whiskers reflect 95% confidence intervals for point estimates. The top row displays the average marginal effect in terms of log differences and the bottom row displays the marginal effect in terms of difference in patents.

distinguishable at the 95% significance level.

Are GCPs Increases Driven by Long-Term Migrants?

We next investigate whether long-term migrant inventors account for the bulk of increases in MNE GCP patenting activity. Given that the examined reforms promote long-term migration, it would follow that the reforms increase globalized patenting by migrant inventors within the subsidiary if they bring their invention network with them after migration. Alternatively, it is also possible that the reforms impact the margin of GCPs not affiliated with long-term migrants. Such GCPs may emerge from either increased short-term and cyclical migration or alternatively through spillovers onto non-migrating inventors promoted by the reforms, where non-migrants increase patenting subsequent to reform events and migrant inventor arrival.

To investigate, we fit variations of Equation 2.1, but regress the specifications on measures of GCP counts produced by migrant inventors as well as on $gcpDiff_{fct}$, a variable constructed as the difference in total GCP counts and migrant GCP counts. For robustness, we evaluate the regressions using both versions of the migrant inventor measures, allowing migrant inventor GCP counts to index (1) all patents within a year of inferred migration, and (2) all patents ever after inferred migration.

Table 2.7 displays the results. Overall, the results suggest that increases in GCP counts are driven both by long-term migrant inventors who have relocated and by inventors who are not within that category. Reforms were previously identified to positively impact GCP production by migrant inventors in Table 2.5, and that effect is reported as column (2), Additional results which vary in time (column 4) demonstrated that this effect is robust to changing specification of the window for measuring migrant patents.[21]

More interesting, however, is the impact on GCP counts which omit the migrant inventor's patent counts ($gcpDiff_{fct}$). The most inclusive definition of omitted migrant GCPs, (column 5, 'All Patents') identifies a positive impact of reforms on GCP counts, such that a single reform at mean exposure is estimated to produce an 18% increase in the annual production of GCPs for subsidiaries with mean exposure. A similar increase is identified for average marginal effects, equating to approximately 0.012 additional patents when excluding all GCPs produced by inventors engaged in long-term migration. This result is relatively large when considered against the patents produced by migrating inventors - the average marginal effect percent increase

[21] In unreported results, a positive effect of reforms on migrant inventor GCP production is still identified for even the most strict window, defined as the first patent subsequent to migration.

Table 2.7: Differential Effects Between Total GCPs and Migrant GCPs

Migrant Patent Window :		w/in 1 Year		All Patents	
	(1)	(2)	(3)	(4)	(5)
Variables	gcp_{fct}	$mig1yr_{fct,gcp}$	$gcpDiff1yr_{fct}$	$migAlw_{fct,gcp}$	$gcpDiffAlw_{fct}$
Cumulative Reforms	0.0056***	0.0023*	0.0050**	0.0030**	0.0048**
$(r_{ct}) \times exp_{fct})$	(0.0016)	(0.00089)	(0.0015)	(0.0010)	(0.0015)
exp_{fct}	-0.35***	-0.046***	-0.34***	-0.071***	-0.33***
	(0.0081)	(0.0026)	(0.0080)	(0.0032)	(0.0078)
Constant	1.56***	0.21***	1.52***	0.31***	1.48***
	(0.032)	(0.0098)	(0.031)	(0.012)	(0.030)
Avg. Marginal Effect of r_{ct}					
	[1.021]	[1.009]	[1.019]	[1.011]	[1.018]
AME	0.0208***	0.0085*	0.0188**	0.0114**	0.0180**
	(0.0059)	(0.0033)	(0.0056)	(0.0039)	(0.0057)
AME in Δ patents	0.0143***	0.0066*	0.0127**	0.0080**	0.0120**
	(0.0041)	(0.0026)	(0.0039)	(0.0027)	(0.0038)
MNE X Year FE	Yes	Yes	Yes	Yes	Yes
Country X Year FE	Yes	Yes	Yes	Yes	Yes
N. Obs	361,452	361,452	361,452	361,452	361,452
Adj. R Within	0.05	0.01	0.05	0.01	0.04

Notes: The table shows the results of high-dimensional fixed effects regressions of arcsinh transformed patent counts on exposure and cumulative reforms among the sample of retained observations (non-singletons). The first column replicates Table 2.5, column 3. Columns 2 and 4 display the results for regressions with migrant inventor GCP counts as the dependent variable with variance in the time measure leveraged to identify migrant GCPs (either by the all patents within a year of a move, or all patents ever after a move). Columns 3 and 5 show models where the DV is GCP counts minus migrant GCP counts. In addition to coefficients, the table displays estimated average marginal effects based on the sample (mean exposure for observations retained in the regression sample is 3.745). Standard errors for estimates are clustered at the subsidiary (MNE-Country) level in parenthesis. Brackets display IRRs. Significance Levels: $+\ p < 0.10$, $*\ p < 0.05$, $**\ p < 0.01$, $***\ p < 0.001$.

is approximately seven percentage points higher among $gcpDiffAlw_{fct}$ relative to $migAlw_{fct,gcp}$, and the relative average marginal effect for GCPs produced at the subsidiary level (0.012 to 0.008) is approximately 1.5 times larger. Similar results are identified for the 1-year window.[22]

Considered together, these results indicate strongly that there are significant spillovers from the pro-long-term business migration reforms onto non-long-term-migrant inventors, and that these spillovers are greater in magnitude than those produced among inventors who do engage in long-term migration. Whether the spillovers occur among short-term and cyclical migrant inventors, among local inventors, or both, remains an open question, although results on domestic patenting are suggestive. As event study and reduced form specifications failed to identify an impact on domestic patenting, the results suggest that the new patents which emerge subsequent to reforms are concentrated among global collaborative patenting. Given this, it seems probable that spillovers are not occurring onto local inventors in a significant way - or that local inventors' production only benefits from spillovers through globalizing of their patenting activities.

[22]Similar results are found for the unreported first-patent window, although results are not significant for the first-patent window.

2.4 Discussion

The purpose of this study is to investigate the interrelationship between shifting barriers or costs to human capital migration and MNE subsidiaries' engagement with globalized knowledge production. We do so through investigating whether and to what extent MNEs' subsidiary-level investments in innovation change following reforms to migration policy that ease barriers to long-term, business-related immigration to a country. We match 14 business-travel-related reforms to migration policy within 9 countries to the patenting activities of 9,179 MNEs and their country-level subsidiaries identified in the database of all USPTO patents. We do so in order to measure how shifts in the barriers to international human capital mobility impact subsequent patenting by MNEs. To estimate the effects of these reforms on MNE patenting, we employ an exposure-based event study design in which subsidiaries within a country are differentially exposed to reform events conditional on their historical dispersion of MNE invention activities. We investigate the impacts of these reforms on MNE subsidiary production of total patents, global collaborative patents, and domestic patents. We additionally explore how the reforms impact the subset of patenting activities driven by inventors observed in the data to permanently migrate.

We find that long-term oriented pro-business reforms to migration policy significantly drive MNE investment within a country, increasing the annual GCPs produced therein by between approximately 0.5% and 5% on average, depending on specification. Consideration of average marginal effects in terms of patents produced suggests that the marginal effect of an additional reform is to increase GCP counts by between 0.0017 and 0.0143 additional GCPs per year after relative to a baseline of 0.56 patents per year. Similar increases are evidenced among overall patents, and the effects prove robust when estimated dynamically over event-time and evaluated for parallel trend violations. When considering long-run migrant inventors' patenting activity, we find similar results of lesser magnitude, but which are strongly identified and different from null effects.

We additionally explore mechanism analyses to determine how treatment effects may vary by hypothesized margins of interest. Given the strong positive association between MNE scale and globalized patenting activity (Kerr and Kerr, 2018), we investigate whether the magnitude of the marginal effects of reforms depends on MNEs' total patenting volume. We find that MNEs with above mean patenting volume are responsible for the large majority of increases in patenting outcomes, producing 2 to 5 times as many patents, global collaborative patents, and domestic patents as their below-mean peers. We then consider whether the positive effects identified are driven primarily by long-term migrant inventors (those who are observed in the patenting data to permanently move) or whether the increases in patenting activity originate with other inventors. The results present strong evidence that inventors other than the 'permanent migrant' inventors drive the majority of increases in patenting. This suggests the existence of significant spillovers from the pro-long-term business migration reforms onto such inventors, and that these spillovers are greater in magnitude than the incentives to patent generated among inventors who do engage in long-term migration. Whether the spillovers occur among short-term and cyclical migrant inventors, among local inventors, or both, remains an open question, although results on domestic patenting are suggestive.

Given these findings, the study produces three contributions. First, via demonstrating the responsiveness of MNEs to changes in the barriers to migration, particularly for global collaborative patenting, the study shows that skilled migration is a key input to the production of global innovations among the modern MNE, and that it causally depends on the context of high-skill human capital mobility policy. Second, the results reinforce the importance of 'absorptive capacity' as a concept that represents the role of the subsidiary within the MNE. This is particularly true among large MNEs, which are shown to significantly benefit relative to small MNEs from easing the barriers to high-skilled business-related migration. This provides support for both the knowledge-based view of the MNE, namely, that MNEs and their subsidiaries exist due to their ability to manage knowledge transfers in the face of international barriers to market transactions, as well as for the moderating role of subsidiaries in receiving and accumulating knowledge (e.g., Kogut and Zander 1992, 1996; Caves 1971; Cohen and Levinthal 1990). Finally, we begin to shed light on the importance of invention spillovers due to shifting barriers to innovation migration within MNEs, particularly originating with short-term migrants or from migrants to non-migrants. Our results suggest a potentially large role of such spillovers from migration policy for MNE innovation.

Some key questions remain unanswered and are related to the limits of the study. The study does not directly assess short-term or cyclical migration, which is likely not captured in the patent data. As a result, whether shifting barriers to migration impact patenting primarily on the margin of the non-migrant (e.g. through learning from migrants and through collaborations) or on the margin of the short-term or cyclical migrant, remains unknown. What this study demonstrates, however, is that the returns to invention of the spillovers onto other inventors substantially exceed the direct benefit of long-term business migration by inventors among a selection of reforms specifically easing such migration. As cyclical and short-term migration is increasingly common and recognized as key to business processes (Gmur and de Sola, 2013; Kerr et al., 2016), it would be helpful for policy makers, managers, and scholars alike to identify upon which margin the reforms primarily induce novel invention among MNEs.

Second, as we rely on specifications involving fixed effects at the MNE-year level, we are unable to identify changes attributable to the MNEs' aggregate production of inventions. As a result, we cannot identify to what extent increased MNE patenting within subsidiary countries is the result of increased aggregate patenting throughout the MNE as opposed to being due to a re-balancing of resources allocated for innovation within the MNE. Determining whether shifting barriers to migration impacts the overall level of innovation is a worthy challenge that could produce significant efficiencies in R&D allocation if known.

Finally, the study encounters generalization limits. As we focus primarily on MNEs of scope and scale, and active in a handful of countries, we are unable to speak to the impacts of the reforms identified on other organizations, such as entrepreneurial and small business. Generalizing of these effects should therefore be conducted with caution. Consequently, future research may leverage the reform database developed for this study to identify how such reforms impact innovation outcomes in context of migrating individuals, in context of other types of organizations (e.g. small businesses), and in context of known mechanisms through which inventive collaborations and knowledge transfer are known to occur and which may augment the productivity of human capital movements, such as the presence of ethnic ties.

Chapter 3

Whom Should I Trust in the Face of the Unknown? Depth, Breadth, and the Evaluation of Novel Ideas

3.1 Introduction

Innovation-intensive organizations face the challenge of developing processes for selection and funding of R&D projects. As innovation at the novelty frontier requires understanding technological and knowledge interdependencies and complexities (Jones, 2009; Murmann and Frenken, 2006), selection and funding is often determined by subject matter experts, individuals with experience and knowledge of the topics under review, who then allocate economically consequential sums. Expert-based review processes account for more than 1.3 million peer-reviewed articles annually (Lardee and Mulligan, 2012), more than $39 billion in annual scientific funding awarded by the National Institutes of Health and National Science Foundation (American Academy for the Advancement of the Sciences, 2017), and almost certainly a substantial fraction, if not the majority, of the approx. $300 billion in annual U.S. private sector R&D expenditures (NSB, 2016). However, subject matter expertise may bias review-based allocation of R&D funding away from novel ideas and projects at the expense of firms' R&D strategies.[1] Prior studies of expert evaluation of innovations, whether in individual (Boudreau et al., 2016) or in panel (Criscuolo et al., 2016) review settings, identify an 'inverse-U' shaped preference for novelty among experts, who generally prefer intermediate-novelty projects over those of high and low novelty. Additionally, greater subject-matter expertise is associated with more critical review and lesser perceived value, as more expert reviewers are hypothesized to perceive more flaws in proposed innovation due to their subject matter expertise (Boudreau et al., 2016). As a result, poorly understood effects of expertise may drive misalignment between organizations' novelty preferences and realized R&D portfolios, producing substantial underinvestment in sufficiently novel invention and scientific research (Nelson, 1959; Rosenberg, 1996), affecting organizational performance (Uotila et al., 2009), economic productivity (Romer, 1990), and societal well-being (Athey and Stern, 2002).

Two tensions emerge in prior research studying expert-based review and experts' preferences for innovations. First, the roles of breadth and depth of knowledge in expert-based R&D evaluation processes are poorly understood and theoretically at odds. Depth of expertise is thought to facilitate evaluation of well-defined problems(Simon, 1997; Chase and Simon, 1973; Khaneman et al., 1982) at the expense of developing breadth; and breadth of expertise is thought to facilitate flexibility in problem solving across domains and in context of unstructured problems (Simon, 1973; Hong and Page, 2009) at the expense of developing depth. Empirically, the literature lacks studies that quantitatively assess the impacts of these structural dimensions of expertise, as prior studies have limited the measurement of expertise in evaluation contexts to univariate measures, primarily intellectual or social proximity (e.g. Boudreau et al. 2016; Li 2017) and typically estimated as cosine similarity or another similar measure of univariate distance. Second, there exists a tension in the hypothesized relationship between expertise and evaluation of novel ideas. As expert review is associated with inverse-U preferences for novelty in innovation (Boudreau et al., 2016), experts are thought generally to be biased against desirable high-novelty exploration and discovery.

This study addresses both tensions by investigating whether expertise is antithetical to the evaluation

[1] In allocating R&D funding, organizations face novelty trade-offs that influence long-run performance *vis a vis* project outcomes (March, 1991). Novel searches are typically greater cost as they are more uncertain, fail at a greater rate, and produce more variant outcomes, but such searches also produce extreme-value breakthrough inventions and discoveries (Fleming, 2001; Wang et al., 2017; Ferguson and Carnabuci, 2017; Mueller et al., 2012). These discoveries can establish a basis upon which future innovations are built, creating substantial value for both firms and society and potentially emerging as 'general purpose technologies' (Bresnahan and Trajtenberg, 1995; Rosenberg and Trajtenberg, 2004). See, for example, the development of the semiconductor, which emerged from highly novel basic science funded by Bell Labs and which now is integral to all computing and computing-adjacent technology(Nelson, 1962; Stokes, 1997).

and selection of novel ideas and exploring how the *structure* of subject matter expertise relates to evaluators' taste for novel innovation projects. Specifically, I examine how scientific evaluators' breadth, depth, and relatedness of subject matter expertise influences their preferences for funding novel innovations. In doing so, I produce new evidence demonstrating that differing human-capital investments in differing dimensions of expertise influence individual experts' preferences across a set of novel innovations generally as well as their taste for novelty in innovation specifically. These results therefore are particularly useful for informing design of R&D and innovation evaluation processes and selection of scientific reviewers, as they suggest how expertise structure may influence selection for novelty in innovation contexts.

To examine these relationships, I analyze the data from an earlier experiment (Boudreau et al., 2016) in scientific grant review at a medical school of a large research university in which 150 early-stage grant proposals were randomized to 142 knowledge-diverse expert evaluators who then engaged in a standardized and blinded individual review process. By leveraging data that connects the evaluators and their publications and also the reviewed proposals to a consistent knowledge taxonomy[2], I am able to construct measures of the breadth and depth of evaluators' knowledge-based expertise, both related to and outside the knowledge of the proposals they review. Using these measures, I am then able to employ fixed effects regressions to estimate how variation in evaluator-proposal level expertise associates with evaluators' perceptions of the impact of the grants they review. Consequently, I produce estimates of this co-variation independent of potential confounders at the level of the evaluator or the proposal (e.g. variation across proposals in unobserved technical quality).

I produce three main findings. First, I find that, contrary to theory, both breadth and depth of innovation-related expertise are associated with more negative perceptions of impact on average, and that such effects are often estimated to occur due to their interaction. For example, a one standard deviation increase in both the breadth and the depth of proposal-related expertise is estimated to decrease assigned impact scores by between 0.15 and 0.56 points. Second, I show that breadth and depth of outside expertise is associated with sizeable increases in the perceived value of the grant proposals reviewed, even when holding fixed the breadth and depth of proposal-related expertise, suggesting that outside expertise has substantial effects on the perceived value of proposed innovations. Finally, I show that breadth of expertise, both related

[2]Namely, the National Library of Medicine's Medical Subject Headings (MeSH) taxonomy associated with the MEDLINE/PubMed database, which indexes the universe of biomedical and scientific academic studies.

and unrelated to innovations under consideration, is associated with moderating the novelty penalty - greater depth or breadth of outside knowledge correlates with increased preferences for both low and high novelty ideas, while greater breadth of proposal-related knowledge in the form of increased knowledge of additional proposal domains potentially negates the novelty penalty.

These results yield a few contributions. First and foremost, the results address the challenge of designing evaluation processes by producing clear implications for managers of R&D evaluation processes tasked with recruiting reviewers. Particularly, the results indicate that certain types of evaluators (those with (1) a breadth of domain knowledge of the evaluated innovation and (2) domain knowledge both related-to and marginal-to the evaluated innovation) are more amenable to highly novel innovations and exhibit less bias against novelty. Consequently, the results provide guidance to managers of R&D funding processes who seek to select for highly novel innovation, who may benefit from recruiting evaluators with a breadth of expertise.

Additionally, the study contributes to a small but growing field of work focused on understanding evaluation in management of innovation and science contexts (Boudreau et al., 2016; Ferguson and Carnabuci, 2017; Wang et al., 2017; Criscuolo et al., 2016; Li, 2017). The current study contributes through (1) refining understandings of how evaluators' knowledge-based expertise influences evaluation via its multi-dimensional structure, and (2) suggesting how one design feature, the selection of evaluators, might be leveraged to overcome ingrained aversion against highly novel innovation. This is especially relevant for the context of peer review in science, where evaluation of high novelty induces substantial disagreement (Lee, 2012). The findings of the study also inform the broader literature on human capital and the direction of inventive activity (Jones, 2009, 2010; Agrawal et al., 2016; Bateman and Hess, 2015; Jones and Weinberg, 2011; Teodoridis, 2018; Azoulay et al., 2010) by exploring how the direction of innovation is determined at a micro level. Specifically, the results provide insight into how heterogeneity in the training and expertise of *evaluators* (as opposed to innovators) may lead to suboptimal levels of exploration in research.

The paper proceeds as follows. Section 2 provides a brief overview of theory surrounding expertise breadth and depth in innovation contexts. Section 3 discusses the study's empirical setting and measurement strategies. Section 4 presents the main methods and results. Section 5 concludes.

3.2 Expertise Structure and Evaluation

3.2.1 Evaluation of Novelty is a Boundedly Rational Search Process

Among the core principles that have emerged from the study of both technological invention (Fleming and Sorenson, 2001; Hargadon and Sutton, 1997; Henderson and Clark, 1990; Schumpeter, 1942; Weitzman, 1998) and scientific discovery (Foster et al., 2015; Jones, 2009; Nelson, 1962; Uzzi et al., 2013) is the understanding that novelty in both technology and ideas emerges from a recombinatorial search process. Starting with a technical problem, inventors combine technical components ('fundamental bits of knowledge and matter', Fleming 2001 p. 25) to produce new technologies that resolve or improve upon current solutions to technological problems and needs (Fleming, 2001; Hargadon and Sutton, 1997). Similarly, scientists begin with a puzzle or phenomenon they seek to explain and combine knowledge bits "embedded in the literature ...in equipment and materials, and ...in the tacit knowledge of individuals engaged in research", (p. 2, Wang et al. 2017) to produce relational mappings and documented patterns that identify, generalize, and explain observed behaviors emerging out of nature (Azoulay et al., 2011; Nightingale, 1998; Wang et al., 2017). These invention and discovery processes exhibit endogeneity, as produced outputs feed back into the technological and scientific knowledge stocks from which new inventions and discoveries are produced (Romer, 1990; Weitzman, 1998). Consequently, the space of possible inventions or discoveries that an evaluator might consider is virtually infinite in size (Weitzman, 1998). Likewise, the input stocks of which an evaluator must be aware are continually growing (Jones, 2009) and are increasingly complex, nested systems with substantial interdependency (Basalla, 1988; Fleming and Sorenson, 2001; Simon, 1962).

In this context, a useful model is to treat evaluators as boundedly rational agents who employ invested expertise and learning about problems to induce structure and establish criteria in their evaluations (Chase and Simon, 1973; Simon, 1972; Newell and Simon, 1973; Simon and Newell, 1971; Gavetti and Levinthal, 2000). Such agents seek out solutions not via optimization over a complete set but rather through the application of structured models of the problem that rely on learning and experimentation within the problem environment (Simon, 1955). In doing so, they leverage mental models (Gavetti and Levinthal, 2000) and developed heuristics (Kahneman and Tversky, 1979) to intuit information regarding the performance of potential solutions.

The mental models and developed heuristics that facilitate this search are believed to vary as a function of the knowledge expertise of individual agents (Hong and Page, 2009; Gilovich et al., 2002; Vuculescu, 2016). In scientific innovation, these 'maps' and 'compasses' are thought to reflect beliefs derived from accumulated tacit cognitive knowledge and behaviors (Nightingale, 1998). Theory suggests (Jones, 2009) and empirical evidence corroborates (Agrawal et al., 2016; Jones, 2010; Jones and Weinberg, 2011) that scientists (and, more broadly, innovators) invest deeply in specific knowledge domains in order to build the cognitive faculty necessary to engage with novel ideas and puzzle-solving on the knowledge frontier. When encountering novel settings, experts tend to 'search under the lamppost', engaging most often and more deeply with ideas in which they have invested human capital (Vuculescu, 2016). Evaluations of novel science, the empirical context utilized in the current study, corresponds with expected behavior in boundedly-rational models. Boudreau et al. (2016), for example, find that that expert evaluators are most critical when their knowledge is most similar to that of the proposals they consider, a tendency they attribute to evaluators perceiving greater nuance among the scientific grants with which they are most familiar.

3.2.2 Dimensions of Knowledge-Based Expertise

Expertise consists of more than just intellectual similarity, however. Theory (Jones, 2009) and empirical studies of intellectual expertise and innovation (Teodoridis, 2018; Bateman and Hess, 2015; Jeppesen and Lakhani, 2010; Leahey, 2017) commonly dichotomize such expertise into two components - depth (also, specialization) and breadth (also, diversity, generalization, marginality, or interdisciplinarity). Expertise must also be considered in conjunction with the puzzle or problem at hand that the innovation under evaluation attempts to solve. Evaluators' expertise may be either 'relevant', directly regarding the knowledge domains of scientific puzzles and proposed solutions under consideration, or it may be 'external' or 'outside', reflecting investments in knowledge topics or components outside the domain of the puzzle or proposed solution under consideration.

Depth Facilitates Critical Review

Consider first the impact of depth of relevant expertise in the evaluation process. Depth is conceptually the extent to which an individual has invested in deep understanding of specific knowledge domains and relationships and is characterized by repetitive investment within a given knowledge domain. Prior theory illustrates that greater depth of relevant expertise provides distinct advantages in the presence of unstructured problems, and that these advantages increase the ability to identify flaws in potential solutions. Relative to novices, experts perceive greater nuance in the underlying problems they consider (Khaneman et al., 1982; Camerer and Johnson, 1991; Gentner and Gentner, 1983), and can rely on knowledge of relational mappings, stored knowledge hierarchies, and mental maps to structure problems near instantaneously (Chase and Simon, 1973; Chi et al., 1981; Simon, 1972). When structured, experts' developed heuristics further facilitate expedient evaluation (Khaneman et al., 1982). These effects appear to be a matter of degree as opposed to binary as some experts possess greater depth than others. Simulations of theoretical models suggest one potential mechanism in the form of 'map refinement'. As total expertise in a subject matter increases, experts' cognitive guides may shift to more accurately resemble the actual interrelationships that govern performance within those knowledge domains (Gavetti and Levinthal, 2000) and this increased accuracy improves the speed with which a solution is selected as well as the performance of that solution (Martignoni et al., 2016). These results suggest that identification of known interdependencies and complexities characterizing innovation problems under review improves as depth of expertise increases, and also suggest that depth facilitates identification of false solution pathways. Evaluators with greater depth of relevant expertise are therefore expected to display greater discernment in the review of proposed novel projects.

Depth Introduces Evaluation Inaccuracies Out of Sample

Investments in depth of expertise reflect investments in dominant knowledge paradigms. Following on Newton's famous quote regarding the sources of his innovations, "If I have seen further it is by standing on the shoulders of giants", Jones (2009) considers the need to accumulate expertise in order to innovate and explore the novel, noting "[a]chieving expertise in an area ... requires an innovator to bring herself to the frontier of knowledge in that area". In other words, the ability to access and consider novel ideas directly benefits from the accumulation of expertise to some extent, for without training and experience, it is impossible to successfully engage in or consider the production of science or invention. However, such training exhibits path-dependency (Dosi, 1982; Nekar, 2003) and instills persistence in beliefs regarding the avenues from which fruitful innovations emerge. Such beliefs can be beneficial in the search for fruitful innovations when areas of specialty are considered (technological component familiarity is associated with more regular inventive success, Fleming 2001), but they also poorly serve experts in the presence of out-of-sample novelty. Cognitive models, when extrapolated beyond the knowledge relationships for which they were developed, are documented to become 'brittle' and subject to breakdown, as they systematically misconstrue or misidentify relationships between knowledge components, causing the predictive performance of models to sharply degrade (Camerer and Johnson, 1991; Brehmer, 1980; Holland et al., 1986; Chi, 2006). Likewise, developed heuristics may guide experts to faulty conclusions regarding solution performance when applied outside of domain (Gilovich et al., 2002; Martignoni et al., 2016). As research further demonstrates, the difficulty of identifying potential solutions depends on the cognitive framing of the problem (Hong and Page, 2009; Marengo et al., 2000), and high-performing solutions to novel problems often emerge from marginal and divergent perspectives (Jeppesen and Lakhani, 2010). Evaluators, when confronting topics outside their knowledge domains, are therefore poorly equipped to consider solution alternatives (Knudsen and Levinthal, 2007).

In science, this inflexibility may be particularly egregious. Individuals entering the profession and seeking to discover new knowledge are habituated into 'normal' paradigms of scientific research in which scientists practice 'puzzle solving' and by nature become critical of work that challenges or exceeds established beliefs about scientific concepts and relationships (Kuhn, 1970; Merton, 1957; Planck, 1950). Yet advancement in scientific knowledge occasionally occurs through revolutions in which established paradigms are challenged and overturned, and foundational beliefs within fields are shown to be flawed (Kuhn, 1970). Radically novel knowledge within this context is often incommensurable with established paradigms, incapable of being disproven under dominant rules. Instead, it faces substantial resistance and engenders disagreement among scientists regarding scientific worth or truth, as it questions dominant beliefs (Kuhn, 1970; Lee et al., 2013). Expertise accumulation reflects and parallels this resistance to challenging paradigms and established ways of doing, and, when used to evaluate highly novel ideas, can become a liability promoting aversion towards novelty. As a result, highly novel ideas introduce radical relationships and connections between knowledge bits and can be penalized by the application of developed expertise that intrinsically underestimates the value of such interconnections (Boudreau et al., 2016). Theory therefore indicates that great depth of expertise negatively associates with preferences for the highly novel.

Breadth Facilitates Identification of Interrelationships

Breadth of expertise, in contrast, represents differentiation across an evaluator's knowledge and measures human capital investments in expertise across knowledge dimensions. Breadth inherently benefits the pursuit and evaluation of novel innovations, as it provides greater access to the knowledge necessary to identify high-performance recombinations. Access to external and different knowledge facilitates problem solving and search processes by facilitating the identification of relevant interactions among problem knowledge domains (Gavetti and Levinthal, 2000) as well as potential recombinatorial opportunities (Granovetter, 1973; Burt, 2004; Hargadon and Sutton, 1997; Teodoridis, 2018). It further encourages familiarity with recombinatorial experimentation (Hargadon and Sutton, 1997). Consequently, boundary-spanning across knowledge dimensions is associated with the identification of higher performance solutions in innovation contexts (Hargadon and Sutton, 1997; Hargadon, 2002; Kaplan and Vakili, 2015; Uzzi et al., 2013) and greater access to disparate and diverse information, thereby possibly allowing evaluators to perceive more potential within novel settings (Fleming et al., 2007; Lingo and O'Mahony, 2010).

Additionally, breadth induces variety in the cognitive models employed by experts when evaluating possible solutions. Greater breadth of knowledge changes the perspectives and cognitive processes experts employ, which influences their evaluations of possible alternatives (Hong and Page, 2009). This shift in perspectives includes shifts in the sets of heuristics employed in search as well as in the cues perceived as relevant to solving a given problem (Gilovich et al., 2002; Hong and Page, 2009), and also facilitates a naivete which may benefit the consideration of innovations (Jeppesen and Lakhani, 2010). As a result, possessing knowledge from the technological and social margins is shown to facilitate the identification of high-performance solutions (Jeppesen and Lakhani, 2010). Therefore, to the extent that evaluators exhibit more diversity in intellectual expertise, it is expected they perceive increased opportunities when evaluating innovations.

Breadth Moderates Novelty Aversion

Breadth can also reduce evaluators' aversion to highly novel ideas. As aforementioned, breadth shifts the heuristics and interpretations that experts employ when considering innovations. Holding depth fixed, increased marginality of knowledge likely fails to induce structural clarity regarding an innovation under consideration. Marginal knowledge may be useful, however, in breaking free from established logics which govern ways of thinking about the relationships among knowledge components, as diversity can encourage divergent thinking (Nemeth, 1986). Social and intellectual marginality, for example, has been shown to increase the likelihood of breakthrough innovations in broadcast search settings, as individuals who approach innovation problems from marginal positions are "not burdened by prior assumptions about effective problem-solving approaches... [and]... approach the problem with different perspectives and heuristics and create a novel solution" (p. 1017, Jeppesen and Lakhani 2010). As increased diversity is expected to yield marginal perspectives and divergent thinking, more diverse evaluators are consequently more likely to prefer highly novel ideas.

Breadth, Depth, and Relatedness of Knowledge

When considering how knowledge expertise relates to the evaluation of the highly novel, human capital investments in knowledge pose an interesting theoretical puzzle. Both depth and breadth provide benefits in evaluation. The former encourages more critical evaluation through the imposition of structure on problems, leverages known heuristics and cognitive maps which have historically proven useful in understanding knowledge domains, and facilitates expedient and nuanced evaluation. The latter encourages greater optimism and foresight in evaluation through facilitating cognitive recombinatory experimentation (Gavetti and Levinthal, 2000) and increasing an evaluator's recognition of interactions and complexity among knowledge components (Page, 2010). This encourages divergent thinking necessary to identify potential in novel ideas.

However, an explore-exploit tradeoff exists in human capital attainment. Theory suggests that investment in knowledge depth occurs at the expense of breadth, and vice versa (Jones, 2009; March, 1991). Empirical studies of knowledge accumulation corroborate this perspective, documenting that investments in expertise become less diverse and deeper when scientific knowledge within a field expands (Jones, 2010; Jones and Weinberg, 2011; Agrawal et al., 2016). Given that greater expertise is associated with an aversion to highly novel ideas, this insight begs the question, what sort of evaluator would be most likely to possess the optimal allocation of intellectual expertise that incorporates the critical insight conveyed by knowledge depth but which avoids the corresponding penalty imposed upon highly novel ideas?

Dividing diversity's effects into innovation-relevant and innovation-unrelated components is suggestive. Simulations of cognitive search processes suggest that diversity among knowledge of problem-relevant components serves to round out perceptions of the interactions among knowledge components, such that cognitive models more accurately reflect the search landscape (Gavetti and Levinthal, 2000). Additionally, theory indicates that balance in innovation-relevant expertise facilitates the adoption and application of uniquely different cognitive perspectives (Page, 2007; Nemeth, 1986) that, conditional on a depth of knowledge sufficient to comprehend the novelty frontier (Jones, 2009), allows perception of recombinatory opportunity not otherwise visible to deep-but-not-broad and broad-but-not-deep experts. Therefore, given two evaluators with equivalent and high depth of proposal-relevant expertise, the evaluator who is more diverse with respect to proposal-relevant domains of knowledge would be expected to prefer highly novel ideas at a greater rate.

Diversity of knowledge unrelated to innovation processes impacts evaluation through a different set of mechanisms. As aforementioned, marginal knowledge may prove particularly beneficial when considering innovation problems through facilitating access to knowledge of distant recombinatory components (Granovetter, 1973; Burt, 2004; Hargadon and Sutton, 1997; Teodoridis, 2018) and inducing variety in the cognitive models and perspectives with which problems are approached (Jeppesen and Lakhani, 2010; Page, 2010; Gilovich et al., 2002). When such knowledge is unrelated to problem components, it still potentially facilitates analogical and inductive thinking in evaluation processes, forms of reasoning that prove particularly pertinent in highly novel settings where deductive processes fail (Arthur, 1994; Gavetti et al., 2005). Analogical reasoning can be defined as the transfer of beliefs about component relationships between two problem-structure contexts which possess some degree of similarity in relational mappings (Gentner, 1983). Problem-solvers match current problems they seek to solve to past solutions by identifying those with similar component relational mappings, but not necessarily similar or like component parts, and intuit beliefs about component relationships in the problem under consideration from the configuration of previously identified solutions in the other problem context (Gentner, 1983; Gick and Holyoak, 1980). Partial or whole mappings of component relationships may be transferred in this way from previously solved solutions to novel problems under consideration where cognitive representations of the problem may largely be absent due to its novelty (VanLehn, 1998). As managers may look across industries and replicate successful business models based upon relational similarity (Gavetti et al., 2005), evaluators of innovations may look across technological problems and scientific puzzles to identify similar past problems and puzzles and infer knowledge and reasoning relevant to interrelationships between components of the current problem (Nightingale, 1998). Such analogies, even when they constitute poor fits, may prove instructive and lead to high-performance solutions (Gavetti et al., 2005). Greater availability of analogies, even when irrelevant to the innovations under review, can lead evaluators to greater appreciation of novelty in the evaluation of new ideas.

3.3 Empirical Context, Data, and Measures

To investigate how breadth, depth, and overlap of expertise impact evaluations of scientific grant proposals, I leverage data from an experiment in which early-stage grant proposals at a medical school within a large research-oriented university were randomized to expert evaluators for review. This section describes briefly the experiment (originally conducted as part of Boudreau et al. 2016) and its key measures and explains in detail the measurements created for analysis. The key independent variables are measures that characterize the depth and breadth of evaluator knowledge relative to the proposals they review, which are constructed based on reviewers' publication records and how they are characterized by the National Library of Medicine's PubMed Medical Subject Headings (MeSH) taxonomy. Depth of knowledge is conceptualized as the accumulation of an evaluator's past experience within specific MeSH knowledge domains based on their prior publications, while breadth of knowledge is measured by the extent to which an evaluator's prior publication record reflects a diversity of MeSH knowledge.

3.3.1 Empirical Context: An Experiment in Scientific Grant Review

This study analyzes the results from an experiment first described in Boudreau et al. (2016), which sought to understand how expertise-based biases impact the scientific grant evaluation process. Here, I briefly describe the experiment and refer the reader to that publication for additional detail.

The setting for the experiment is review of early-stage grants ('seed grants') focused on making progress in research on endocrine-related disease, specifically Type 1 Diabetes (T1D). In a first stage, researchers partnered with a large university medical school to solicit proposals on the topic and a call was extended to the wider university research community from which submissions were solicited. The call was structured as a competition with incentives including a cash prize ($2,500 to each of 12 winners), signaling benefits, and the potential to later win seed grants totaling $1 million in a second phase call. The call included instructions to follow a shortened and standardized proposal format (Langfeldt, 2001) in order to facilitate standardization and limit biases in the review process.[3] The call yielded 150 early-stage solo-authored grant

[3]Although the proposals were constrained to the study to focus on Type-1 Diabetes for subject purposes, the call for proposals was broadly framed and extended to members of the broader university community via email. Proposal content was generally otherwise unconstrained in the call, and could be related to diagnosis, treatment, and prophylaxis. The advantage of this framing is that it produced research proposals that are constrained in problem-domain, but which exhibit substantial variety in their methods and the knowledge relationships they sought

proposals, of which 72 originated from the host university and for which the modal submitter was a junior faculty member. Appendix C.1 discusses an example proposal solicited.

In a second stage, expert reviewers were recruited and engaged in an evaluation process. As the original study sought variation in evaluator expertise, experts from the university faculty were invited from three groups stratified by seniority (junior vs. senior) and intellectual distance to the core topic: (1) those with at least one publication in the problem domain, (2) those without publications in the domain, but with co-authors with a publication, and (3) those without publications or links to the problem. Faculty were invited within-strata according to numbers of publications, and of 180 invitations, 142 individuals participated in the experiment, who were substantially diverse in age, gender, and ethnicity as well as in training (measured by degrees awarded). The grant proposals were then block-randomized to evaluators in 10 blocks of 15 proposals each (averaging 14.2 evaluations per proposal). Evaluators then reviewed and scored all proposals in the block they received, assessing each proposal by (i) potential impact and (ii) feasibility.[4] To control for potential socially related or identity-based biases, randomization and review were triple blind - evaluators were only given access to their 15 assigned proposals, were not given information about nor interacted with other evaluators, and submitters' names were blinded from proposals.

This match of evaluators to proposals yielded a dataset consisting of 2,130 evaluator-proposal pairs. Publications records were available for 137 evaluators at the time of the experiment. Excluding evaluators without available publication records at the point of review (5 individuals) reduced the number of observations to 2,055 ratings at the evaluator-proposal level.

3.3.2 Data and Key Measures

As the central focus of this study is to understand how the structure of expert knowledge associates with evaluators' perceptions of the proposals they review, I characterize evaluator knowledge along three key dimensions - breadth, depth, and relatedness to the proposals under review. To measure these dimensions, I proxy for evaluator knowledge with the aggregated measures of the knowledge embedded in evaluators' prior publications. By leveraging the NLM PubMed database and the corresponding MeSH taxonomy that

to explore.

[4]Specifically, evaluators were instructed to rate these criteria on 10-point scales. For example, the prompt for impact was: "On a scale of 1 to 10 (1 [being the] lowest to 10 [being the] highest) please assess the impact on disease care, patients, or research".

it employs to characterize the knowledge of all articles it indexes, evaluator knowledge can be characterized and measured relative to the stock of all biomedical knowledge (the publications indexed in PubMed). Additionally, as the experiment involved recruiting NLM librarians to assign MeSH keywords to all submitted proposals, the MeSH taxonomy can also be used to measure the relevance of evaluator knowledge to the proposals they examine. Below, I detail the key measures of interest employed in analyses.

Dependent Variable: Perceived Impact

The primary outcome measure is $Impact_{ep}$, defined as the scores assigned by evaluators reflecting their perception of the impact of the proposals under review. It is a measure on a 1 to 10 scale, with a greater score reflecting greater perceived impact. The assigned scores are roughly normally distributed with a rightward skew but also a heavy left tail of bottom-rated observations (mean = 5.655 median = 6, sd = 2.585). Scores assigned to proposals exhibit significant variance across proposals and among evaluators, reflecting substantial noise not explainable solely by differences among proposals. Reference Section 3.4.1 and Figure 2 of Boudreau et al. (2016) for additional analysis of impact scores.

Independent Variables: Structure Measures of Evaluator Knowledge

Key independent variables measure four concepts - novelty, breadth, depth, and relevance of knowledge. To create measures, I draw on the 2013 PubMed database, which indexes metadata on just over 21.5 million biomedical publications, and the corresponding NLM MeSH keyword taxonomy, which is used to classify the technical knowledge embedded within each of the publications indexed by PubMed.[5] The MeSH knowledge taxonomy is composed of 16 top-level categories describing core concepts in biomedical science, as well as additional keywords which 'branch' from each of these categories into up to 13 lower levels. Keywords at a lower level within a branch reflect a concept nested within the keywords at a higher level. For example, the MeSH term "C19.246.267 - Diabetes Mellitus, Type 1", is nested below "C19.246 - Diabetes Mellitus",

[5]Specifically, I use the 2013 MEDLINE Baseline Repository (MBR) snapshot, which indexes PubMed metadata on all publications in PubMed and their corresponding MeSH terms up through November 2012, shortly after the original experiment was conducted. Leveraging the 2013 MBR snapshot 'freezes' the stock of knowledge at approximately the point of the experiment, providing accurate estimates of the overlap in knowledge domains between evaluators' expertise (derived from their PubMed publications) and proposal content. To ensure comparability between knowledge measures in evaluators' publications and the submitted proposals, the MeSH terms assigned to proposals were updated to the 2013 MeSH tree taxonomy. The MBR repository and the 2013 MeSH keyword taxonomy tree can be accessed at `https://mbr.nlm.nih.gov/`.

which in turn is nested below the subcategory “C19 - Endocrine System Diseases” for which the top-level MeSH category is category ‘C - Diseases Category‘.

To understand how this structure facilitates characterization and measurement of knowledge, consider the career of George Church, a well-known scientist in the field of genetics, and assume that his career has been (hypothetically) limited to only three publications.[6] The first is the 2009 article, “Genome-wide identification of human RNA by parallel DNA capturing and sequencing”, published in volume 234, issue 5931 of Science, for which the PubMed entry is shown in Appendix C.2. The article, assigned the PubMed Identifier (PMID) 19478186, was also assigned 17 MeSH terms that reflect the topics the article covers, interpreted as its embedded knowledge. Further consider two imaginary publications, identified by the fictitious pmids ‘E0001’ and ‘E0002’. Table 3.1 displays the MeSH terms which would be mined from an analysis of the three articles, with check tags (common terms applied broadly across articles) and modifier terms (keywords modifying to the MeSH focus of the article) excluded.

Based on this collection of terms, and their assignment to articles, Mr. Church’s knowledge-based experience can be encapsulated by a vector aggregating the terms, represented by m_e in the table. Additionally, Mr. Church’s expertise can be compared relative to the vector of MeSH terms assigned to proposals that he might review as an evaluator, such as $m_{p(30)}$, which is the vector of MeSH assigned to the proposal submission #30 of the experiment. When multiplied across the common MeSH domains of Mr. Church’s expertise (m_e) and that of the knowledge encompassed by the proposal ($m_{p(30)}$), the result is the vector of Mr. Church’s ‘proposal-relevant’ expertise, denoted m_{ep}.

Such vectors serve as the basis under which the knowledge-based expertise of all evaluators in this study is characterized. For each of the evaluators, their complete publication record is matched to the corresponding records within PubMed, and these matches are used to create MeSH term frequency vectors. These vectors then serve as the basis upon which knowledge measures are computed. Where a measure is denoted by e, it is computed across the evaluator’s full expertise vector (i.e., m_e), whereas measures denoted by ep are the ‘proposal-related’ knowledge of the evaluator and are computed across the vector equivalent of m_{ep}. Proposal-unrelated knowledge is that which is within the domain of m_e but not within the domain of m_{ep}, and is denoted $m_{e \notin p}$.

[6] In actuality, PubMed indexes 406 publications for “Church, GM” as of April 10, 2020.

Table 3.1: Example of Measuring Expertise Using MeSH Terms

	PMID					
MeSH Term	19478186	E0001	E0002	m_e	$m_{p(30)}$	m_{ep}
Adenosine Deaminase	1		1	2		
Adrenal Glands	1			1		
Alu Elements	1			1		
Amino Acid Sequence		1	1	2		
Autoantibodies			1	1		
Base Sequence	1	1		2		
Brain	1	1		2		
Case-Control Studies			1	1		
Cell Cycle Checkpoints		1		1		
DNA	1	1	1	3		
DNA, Complementary	1		1	2		
DNA Damage		1		1		
Diabetes Complications		1		1		
Diabetes Mellitus, Type 1		1	1	3	1	3
Diabetes Mellitus, Type 2					1	
Genome, Human	1	1		2		
Gene Expression Regulation			1	1		
Genetic Predisposition to Disease			1	1	1	1
Genetic Testing			1		1	1
Genetic Variation					1	
HLA-DQ Antigens					1	
High-Throughput Screening Assays			1	1		
Intestine, Small	1			1		
Insulin, Genetic			1		1	1
Minisatellite Repeats					1	
Molecular Sequence Data			1	1		
Neurons		1		1		
Peptide Library			1	1		
RNA Editing	1	1		2		
RNA, Double-Stranded		1		1		
RNA-Binding Proteins			1	1		
Sequence Analysis, DNA	1	1		2	1	2
Zebrafish			1	1		

Notes: The table illustrates an example of how the structure of evaluator and proposal knowledge is measured using the MeSH taxonomy. The first column displays a series of MeSH terms assigned to PubMed publications (identified by PMIDs), and columns 2 - 3 display the assignment of MeSH terms to publications. The fourth column, m_e, is the vector representing the evaluator's knowledge-based expertise, equivalent to the sum of the evaluator's publications. The next column, $m_{p(30)}$, shows the vector of MeSH terms corresponding to the example proposal in Appendix C.1, which the evaluator hypothetically examines. The final column displays the MeSH vector representing the evaluator's knowledge-based expertise related to the proposal, which is equivalent to $m_e \times m_p$.

Breadth of Expertise: To measure the breadth (or scope) of knowledge-based expertise, I create three measures drawn from the study of diversity (see Stirling 2007 for a review). Diversity consists of measurement along three dimensions. These are: variety, which reflects the number of types; balance, which reflects the distribution among types; and disparity, which reflects the distance between the types. Diversity and breadth are increasing along each of these dimensions. As an evaluator gains experience in more MeSH term domains, as they gain greater balance in their experience among those terms, and as they focus on terms at greater distance from one another, their expertise conceptually embeds greater 'breadth'. To characterize this breadth, I compute the following measures:

- **Variety ($Variety$) -** Variety is conceptually the count of an expert's knowledge domains. In this case, this is the count of unique MeSH terms in an evaluator's record which is equivalent to the length of the MeSH frequency vector. For the imaginary career of Mr. Church, $variety_e = 27$ and, if Mr. Church were a reviewer in the experiment evaluating proposal submission #30, Mr. Church's proposal-related variety of expertise would be $variety_{ep} = 5$.

- **Diversity Index ($DivIndex$) -** To measure influence of expertise balance on evaluators' reviews, I compute Simpson's Diversity Index, measured as the sum of the squared proportions of a vector of types: $DivIndex = 1 - \sum^{I} p_i^2$ where i reflects individual MeSH terms within a vector and p_i is their relative proportion.[7] From the example, $DivIndex_{ep} = 0.75$.

- **Rao-Stirling Diversity ($RSIndex$) -** The final measure is the Rao-Stirling diversity measure, outlined in Stirling (2007) and measured as: $RSIndex = \sum_{ij,i \neq j} d_{ij} \cdot p_i \cdot p_j$ where p represents the relative proportion of MeSH terms i and j within a vector, and d_{ij} is the distance between MeSH terms. To compute d_{ij}, I measure the edge-wise distance between the two MeSH within the MeSH taxonomy tree.[8] The advantage of this measure is that it incorporates the disparity (or distance) between MeSH knowledge domains and places equal importance on variety, relative balance, and disparity.

- **Distance Between Knowledge Clusters** ($DistClust_{ep}$) - The final diversity measure computed

[7]Balance indices fall within the class of entropy measures, and all measures of balance inherently capture, to some extent, the variety of a series of types. However, certain measures are weighted more heavily towards estimating relative proportion over variety. For example, Simpson's Diversity Index, which is equivalent to one minus the Herfindahl-Hirschman Index of concentration, places greater relative weight on proportion to variety than does Shannon's entropy.

[8]In the event that a term is multiply listed, the shortest distance between two terms is leveraged in computation.

is the mean distance between the evaluator's proposal-related knowledge and that of the evaluator's largest cluster of knowledge, defined as their five most frequent MeSH terms, that are unrelated to the proposal they review. The measure is functionally the mean edge-based distance between MeSH, based on their relative position in the MeSH taxonomy.

Depth of Expertise: I additionally measure the depth of evaluators' proposal-relevant experience. In the biomedical sciences and among biomedical scientists, repeated publication, experience, and investment within the same knowledge domain serves as a proxy for depth of intellectual expertise. As a result, depth of expertise naturally (but moderately) correlates with measures of experience, such as years elapsed since the completion of a graduate degree. Given this correlation, I examine two measures of expertise depth:

- **Depth Freq (**$DepthFreq$**) -** the first measure is simply the sum of MeSH frequencies embedded within a vector. For the example, $DepthFreq_e = 39$ and $DepthFreq_{ep} = 8$.
- **Depth Mean (**$DepthMean$**) -** The second measure is computed as the mean of the relevant vector of MeSH terms (i.e., $DepthMean = DepthFreq/Variety$). A complication of the $DepthFreq$ measure is that it nominally correlates and scales with variety and experience, and therefore may confound breadth and depth. This measure controls by normalizing depth by variety, producing an estimate of the average depth of an evaluator's expertise. For the example, $DepthFreq_e = 1.\overline{4}$ and $DepthFreq_{ep} = 1.6$. This is the baseline depth measure.

Independent Variables: Novelty and Additional Covariates

As moderators of the documented aversion toward novelty are a major concern of this study, novelty among proposals is a key parameter of interest. As innovation scholarship theorizes that novelty emerges from recombination, I measure novelty via the presence of first-in-class MeSH term recombination. Specifically, novelty is measured as:

- **Local Novelty (**$Novelty_{ep}$**) -** The local novelty of an evaluator-proposal pair, $Novelty_{ep}$, represents knowledge relationships that are novel to an evaluator on a proposal under consideration, computed as the count of MeSH pairs assigned to a proposal under consideration (of all possible MeSH combinations) which are not assigned to any of the evaluator's prior publications.

- **Global Novelty ($Novelty_p$) -** The global novelty of a proposal, $Novelty_p$, is the ratio of the count of paired MeSH terms assigned to a proposal that had not previously been co-assigned within any publication among all prior PubMed publications up to the date of the experiment over the total count of all MeSH pairs assigned to the proposal.

Other Covariates This study relies substantially on fixed-effects analysis, the randomization of proposals to evaluators, and the experiment's triple-blind nature to control for potential confounders in estimation. Covariates controls are used at points depending on specification, however. Table 3.2 displays key control covariates including measures of proposal quality, namely, the number of citations the proposal author accrued in the seven years prior to the experiment and the maximum number of citations that accrued to any one of the proposal author's prior publications. These quality data were originally drawn from the indexing systems at the university where the experiment was conducted. However, many proposal authors were not members of that institution. I therefore supplemented these citation counts by retrieving additional equivalent data from the Web of Science database for proposal authors for whom data were missing.[9]

Table 3.2 displays key statistics for different levels of the panel. As with other settings in knowledge work and innovation, several statistics exhibit a long-tail rightward skew with large outliers. Of note, key variables including those measuring depth, breadth, proposal submitter citations and the global novelty of proposals have a long rightward tail. Table 3.3 displays the correlation of key variables. Notably, in line with prior evidence, depth of knowledge expertise on the subjects specific to the proposal ($DepthMean_{ep}$) is negatively correlated with estimated impact. However, a similar correlation is observed when evaluators possess depth of outside expertise ($DepthMean_{ep}$), although this correlation may be due to extreme collinearity with an evaluator's overall depth of expertise ($DepthMean_e$). Diversity measures exhibit less consistency and relatively low levels of correlation.

[9]This was completed for authors who could reasonably be uniquely identified with confidence by last name in conjunction with other biographical data, such as reported institution. Adding this additional data increased citation measure coverage of proposals to 85 out of 150.

Table 3.2: Summary Statistics

Statistic	N	Mean	St. Dev.	Min	p25	Median	p75	Max
Proposal Level, N = 150								
Length (Characters)	150	8219.76	15093.48	617.00	3454.00	5801.00	9222.00	177604.00
Num. References	150	5.58	9.77	0.00	0.00	0.00	8.00	73.00
Num. Figures	150	0.28	0.84	0.00	0.00	0.00	0.00	8.00
Has Structure Elements	150	0.49	0.50	0.00	0.00	0.00	1.00	1.00
Has Background Section	150	0.21	0.41	0.00	0.00	0.00	0.00	1.00
Submitter Max Citation Count	85	205.20	275.53	0.00	19.00	101.00	348.00	1328.00
Submitter Sum Citation Count	85	1757.95	2883.65	0.00	23.00	342.00	2094.00	12182.00
Num. MeSH	150	13.63	5.51	4.00	10.00	12.00	17.00	33.00
Novelty - Global Ratio ($Novelty_p$)	150	0.16	0.11	0.00	0.08	0.15	0.22	0.47
Evaluator Level, N = 137								
Years Since Grad.	137	23.53	12.68	2.00	12.00	24.00	33.00	58.00
Publications	137	104.37	139.23	1.00	15.00	62.00	153.00	856.00
T1D Publications	137	3.95	11.20	0.00	0.00	0.00	1.00	86.00
Senior	137	0.53	0.50	0.00	0.00	1.00	1.00	1.00
Female	137	0.37	0.49	0.00	0.00	0.00	1.00	1.00
Second Degree	137	0.07	0.26	0.00	0.00	0.00	0.00	1.00
Primarily Research?	137	0.62	0.49	0.00	0.00	1.00	1.00	1.00
Primarily Patient Care?	137	0.62	0.49	0.00	0.00	1.00	1.00	1.00
Expertise Breadth - Variety ($Variety_e$)	137	338.67	299.36	8.00	83.00	267.00	526.00	1411.00
Expertise Depth ($MeanDepth_{ep}$)	137	2.40	1.33	1.00	1.43	1.97	3.10	8.27
Evaluator-Proposal Level, N = 2,055								
Impact Score ($Impact_{ep}$)	2055	5.66	2.58	1.00	3.00	6.00	8.00	10.00
Novelty - Local Count ($Novelty_{ep}$)	2055	84.29	78.92	2.00	34.00	55.00	120.00	496.00
Depth - Freq. ($DepthFreq_{ep}$)	2055	15.18	37.40	0.00	0.00	1.00	10.00	549.00
Depth - Mean ($DepthMean_{ep}$)	2055	4.22	9.74	0.00	0.00	1.00	4.00	183.00
Depth - Mean, Unrelated ($DepthMean_{e \notin p}$)	2055	2.38	1.31	1.00	1.43	1.95	3.06	8.33
Breadth - Variety ($Variety_{ep}$)	2055	1.86	2.39	0.00	0.00	1.00	3.00	17.00
Breadth - Diversity Index ($DivIndex_{ep}$)	2055	0.59	0.39	0.00	0.24	0.63	1.00	1.00
Breadth - Rao-Stirl. Index ($RSIndex_{ep}$)	2055	0.93	1.28	0.00	0.00	0.00	2.00	6.19
Breadth - Dist., Top 5 ($DistClust_{ep}$)	2055	8.72	0.82	6.30	8.13	8.65	9.24	11.84
Depth - Mean, Top5 ($DepthTop5Clust_{e \notin p}$)	2055	29.97	44.16	1.00	4.00	15.40	37.80	326.20
Proposal Cites Evaluator?	2055	0.00	0.03	0.00	0.00	0.00	0.00	1.00
Submitter & Evaluator Co-Author?	2055	0.01	0.07	0.00	0.00	0.00	0.00	1.00
Submitter & Evaluator Same Institution?	2055	0.02	0.13	0.00	0.00	0.00	0.00	1.00

Notes: The table displays summary statistics of different elements of the panel. Measures listed with a '?' are binary indicators.

Table 3.3: Correlation Among Key Variables

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) $Impact_{ep}$	1.00											
(2) $Novelty_p$	-0.06	1.00										
(3) $Novelty_{ep}$	0.13	0.15	1.00									
(4) $DepthMean_e$	-0.12	0.00	-0.00	1.00								
(5) $DepthMean_{ep}$	-0.14	0.01	-0.04	0.38	1.00							
(6) $DepthMean_{e \notin p}$	-0.12	0.00	-0.00	1.00	0.35	1.00						
(7) $Variety_e$	-0.13	-0.01	-0.02	0.77	0.35	0.77	1.00					
(8) $Variety_{ep}$	-0.03	-0.02	0.32	0.45	0.32	0.43	0.52	1.00				
(9) $DivIndex_{ep}$	0.02	-0.02	0.01	-0.13	-0.26	-0.12	-0.16	-0.14	1.00			
(10) $RSIndex_{ep}$	-0.03	-0.00	0.26	0.37	0.21	0.36	0.46	0.81	-0.00	1.00		
(11) Submitter Cites - Sum (ep)	-0.06	-0.11	0.04	0.02	-0.00	0.02	0.02	-0.01	0.01	-0.02	1.00	
(12) Submitter Cites - Max (ep)	-0.04	-0.14	0.15	0.00	-0.02	0.00	-0.00	0.06	-0.01	0.06	0.67	1.00

Notes: The table displays the correlation among key variables of interest. Submitter Cites - Max is the max number of citations a proposal submitter ever received to a single paper.

3.4 Main Results

3.4.1 Innovation-Related Breadth and Depth of Expertise Negatively Associate with Impact

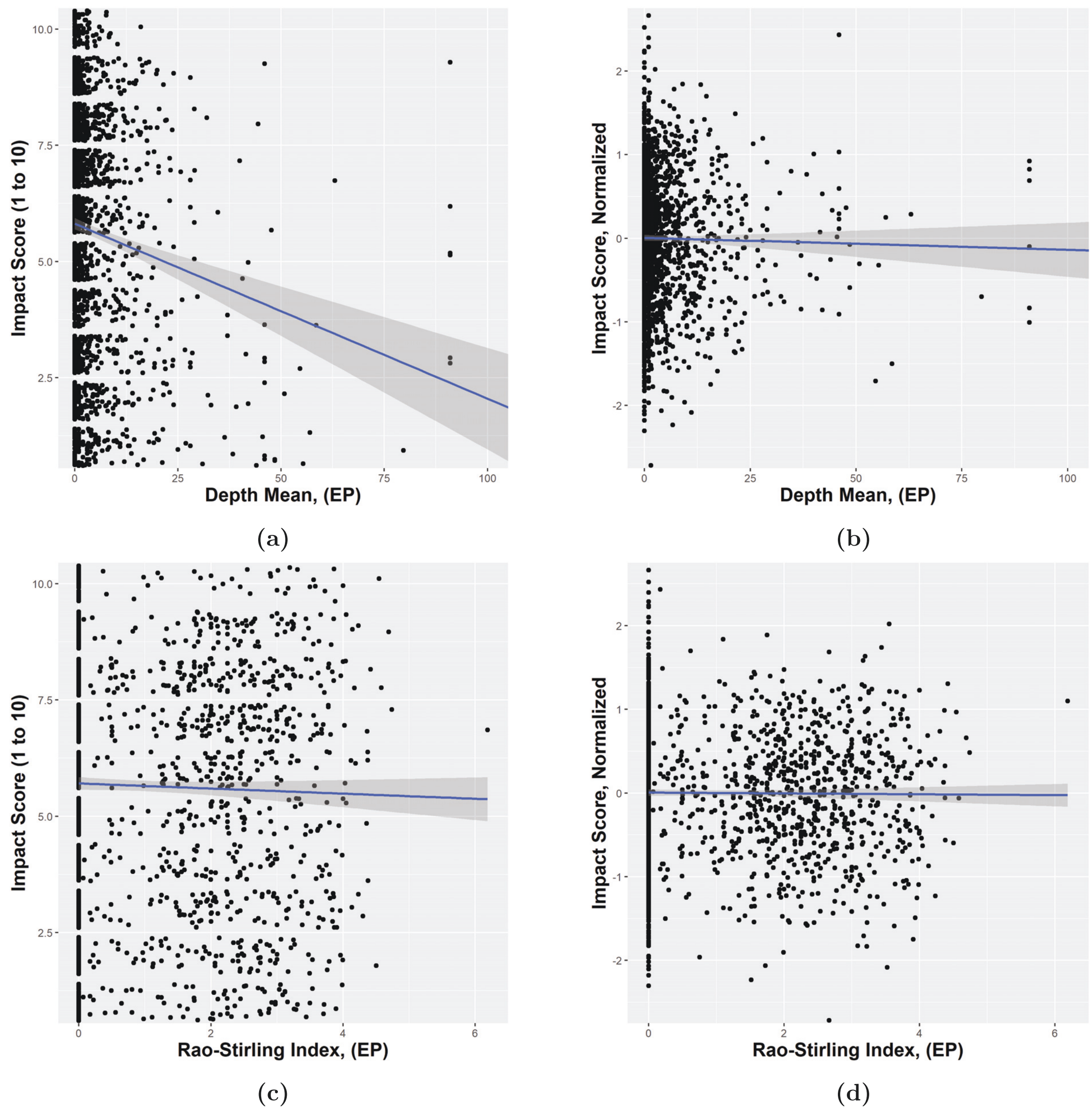
I first investigate whether the structure of related evaluator expertise impacts their preferences for proposals. Consider Figure 3.1, which plots the impact scores assigned to the proposal against measures of evaluators' breadth ($RSIndex_{ep}$) and depth ($DepthMean_{ep}$) of proposal-related expertise. The figures are accompanied by single regression trendlines with 95% confidence intervals. Subfigures (a) and (c) plot unadjusted but jittered scores, and subfigures (b) and (d) plot scores which have been adjusted by first standardizing by the evaluator and then demeaning by the proposal to control for proposal and evaluator fixed effects in scoring.

The two structural dimensions of expertise show a negative association with estimated impact; however this association is only identifiably different from a null effect for depth in the specification which does not include adjustments to impact scoring. These associations are therefore only suggestive. Similarly, while unreported evaluation of quantile means across each dimension do identify some slight variations, they do not reveal a consistent trend.

One reason for the lack of identification may be the lack of sufficient controls. I therefore turn to multiple regression leveraging fixed effects for estimation purposes. Specifically, I estimate variations of:

$$Impact_{ep} = f(\beta_0 + \beta_1 Depth_{ep} + \beta_2 Breadth_{ep} + \beta_3 DepthXBreadth_{ep} + \gamma_p + (\gamma_e \; or \; X_e);\; \epsilon_{ep}) \tag{3.1}$$

where βs are the coefficients of interest, γ_p and γ_e are proposal and evaluator fixed effects, X_e are evaluator-level covariates, and ϵ_{ep} is an evaluator-proposal level error term. The advantage of leveraging fixed effects in this specification is two-fold. First, it is difficult to directly observe the true value of the proposed novel research, and scores almost certainly are causally impacted by proposal technical value. Second, evaluator idiosyncrasies consistent across the evaluation process (such as different beliefs on scale meaning) and evaluator characteristics related to the academic profession (e.g. experience, publication record) likely drive differences in the outcome. Controlling for fixed-effects resolves both complications, allowing for clean



(a) (b) (c) (d)

Figure 3.1: Impact Scores, Breadth, and Depth

Notes: The four figures plot evaluators' ratings of the perceived impact of proposals against measures of the breadth ($RSIndex_{ep}$, subplots c and d) and the depth ($DepthMean_{ep}$, subplots a and b) of evaluators' proposal-related knowledge. The figures are accompanied by ordinary-least squares trend lines of y = f(x), accompanied by 95% confidence intervals in grey. The vertical axis of subplots (a) and (c) is impact score, jittered for visualization purposes. The vertical axis of subplots (b) and (d) is the impact score first standardized by evaluator and then demeaned by proposal (mean = 0; sd = 0.75; min = -2.7; max = 2.66).

Table 3.4: Impact Scores as a Function of Depth of Related Knowledge

	$Depth = DepthMean_{ep}$			$Depth = DepthFreq_{ep}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$Depth_{ep}$	-0.37***	-0.11+	-0.049	-0.33***	-0.22***	-0.17**
	(0.060)	(0.063)	(0.059)	(0.057)	(0.061)	(0.060)
cons	5.66***	6.25***	6.11***	5.66***	6.14***	6.01***
	(0.056)	(0.39)	(0.78)	(0.057)	(0.40)	(0.78)
Eval. Controls	No	Yes	No	No	Yes	No
Evaluator FE	No	No	Yes	No	No	Yes
Proposal FE	No	Yes	Yes	No	Yes	Yes
N. Obs	2,055	2,055	2,055	2,055	2,055	2,055
Adj. R	0.02	0.30	0.47	0.02	0.31	0.47

Notes: The table displays regression of impact scores on both variations of the depth measure. Evaluator controls leveraged include years since graduation, number of publications, number of T1D publications, whether the evaluator is a senior faculty member, and evaluator gender. Results are robust to specification via an ordered logistic model (unreported). Robust standard errors in parenthesis.
$+\ p < 0.10$, $*\ p < 0.05$, $**\ p < 0.01$, $***\ p < 0.001$

identification of the association between the proposal-related portion of the structure measures and remaining variation in scores. For ease of interpretation, all regressions are run with standardized independent variables.

Table 3.4 presents the results of regressing impact on depth, and the results align with the suggestion trend of Figure 3.1a. Greater depth of proposal-related knowledge is significantly associated with decreases in the perceived impact of the proposal under review. Related depth individually explains approximately 2% of the variation observed in impact scores, which is on the high end for studies of scientific evaluation.[10] Depending on the specification considered, a one standard deviation increase in depth of related knowledge is equivalent to between an 0.11 and 0.37 point decrease in perceived impact, representing shifts of between 2% and 6.5% relative to the average score assigned (and approximately 4% to 14% of the observed standard deviation in impact scores).

Table 3.5 presents the results from fitting a similar model but focusing on the breadth measures as the key input. Here, the evidence again agrees with the results suggested by the initial figures. The results suggest that there is no identifiable connection between $variety_{ep}$ and evaluator preferences, or at least the effect

[10]This *adj.* r^2 range may seem low but is on par with independent variables from other studies of scientific evaluations. Boudreau et al. (2016), for example, found *adj.* r^2 ranging from a half to two percent when regressing evaluation outcomes on knowledge distance, an aggregate of the measures considered here. Similarly, regressions in Li (2017) explore similar relationships in the evaluation of novel science and can only explain around ten to fifteen percent of variation in outcomes when evaluator and proposal fixed effects were included.

Table 3.5: Impact Scores as a Function of Breadth of Related Knowledge

	$Variety_{ep}$		$DivIndex_{ep}$		$RSIndex_{ep}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Breadth	0.028	-0.054	-0.039	-0.12*	0.023	-0.030
	(0.074)	(0.071)	(0.053)	(0.052)	(0.065)	(0.063)
cons	6.23***	8.87***	6.21***	9.00***	6.23***	8.89***
	(0.40)	(0.62)	(0.40)	(0.62)	(0.40)	(0.62)
Eval. Controls	Yes	No	Yes	No	Yes	No
Evaluator FE	No	Yes	No	Yes	No	Yes
Proposal FE	Yes	Yes	Yes	Yes	Yes	Yes
N. Obs	2,055	2,055	2,055	2,055	2,055	2,055
Adj. R	0.30	0.47	0.30	0.47	0.30	0.47

Notes: The table displays regression of impact scores on various breadth / diversity measures. Evaluator controls leveraged include years since graduation, number of publications, number of T1D publications, whether the evaluator is a senior faculty member, and evaluator gender. Similar results in magnitude, significance, and sign, are obtained if specified as an ordered logistic model (unreported). Robust standard errors in parenthesis. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

is likely small and difficult to identify. Similar results are also obtained for $RSIndex_{ep}$, the comprehensive diversity measure which incorporates variety, disparity, and balance. However, balance appears to have a strong impact on the ratings evaluators assign, with a standard-deviation improvement in balance yielding a 0.12 decrease in perceived impact (or just over a 2% decrease relative to the mean score).

Leveraging both measures and fitting the full specification of Equation 3.1 allows for consideration of whether expert knowledge relies on interactions between breadth and depth of related knowledge. The corresponding results are shown in Table 3.6.

The results vary depending on the dimensions of diversity incorporated into the breadth measure. When considering only variety, the results suggest that differing perceptions of impact are driven solely by the interaction between depth and breadth, such that a standard deviation increase in both results in a 0.18 decrease in perceived impact. When weighting the diversity measure to focus on balance (via $DivIndex_{ep}$), a similar effect is estimated for the interaction and substantive effects are estimated along each dimension, such that a standard deviation increase in the depth of proposal-related knowledge yields a 0.24 point decrease in perceived impact conditional on mean breadth, and a standard deviation increase in the diversity of proposal-related knowledge yields a 0.16 point decrease in perceived impact conditional on mean depth. When incorporating disparity into the diversity measure (via $RSIndex_{ep}$), the estimated

Table 3.6: Impact Scores as a Function of Breadth & Depth of Related Knowledge

Dimensions:	Variety		Balance		All, incl. Disparity	
Variable:	$Variety_{ep}$		$DivIndex_{ep}$		$RSIndex_{ep}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$Depth = DepthMean_{ep}$	-0.051	-0.014	-0.076	-0.24*	-0.050	-0.095+
	(0.059)	(0.066)	(0.063)	(0.10)	(0.059)	(0.057)
$Breadth_{ep}$	-0.056	0.028	-0.13*	-0.16**	-0.031	-0.014
	(0.071)	(0.077)	(0.053)	(0.056)	(0.063)	(0.063)
$Breadth_{ep} \times Depth_{ep}$		-0.18***		-0.16*		-0.15**
		(0.053)		(0.076)		(0.053)
cons	8.85***	8.96***	8.98***	8.85***	8.88***	8.89***
	(0.62)	(0.63)	(0.62)	(0.63)	(0.62)	(0.63)
Evaluator FE	Yes	Yes	Yes	Yes	Yes	Yes
Proposal FE	Yes	Yes	Yes	Yes	Yes	Yes
N. Obs	2,055	2,055	2,055	2,055	2,055	2,055
Adj. R	0.47	0.47	0.47	0.47	0.47	0.47

Notes: The table displays regression of impact scores on both breadth and depth measures. Evaluator controls leveraged include years since graduation, number of publications, number of T1D publications, whether the evaluator is a senior faculty member, and evaluator gender. Similar results in magnitude, significance, and sign, with some improvements in the significance of depth measures, are obtained if specified as an ordered logistic model (unreported). Robust standard errors in parenthesis. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

effect of the interaction remains, the estimated independent effect of breadth is statistically insignificant, and the estimated impact of standard deviation increases in depth is to yield a decrease in perceived impact by approximately 0.095 points conditional on mean depth.

These results are in-line with the overall suggestion that both breadth and depth of knowledge related to innovations under review are associated with decreases in the perceived value of innovations. While depth of knowledge appears to be strongly related to decreased estimates of value on average, breadth of knowledge appears to primarily modify the strength of the impacts of depth, but for the dimension of balance within breadth, which correlates negatively with perceived impact as balance among knowledge domains increases. Overall, the results support the perspective that knowledge-based expertise facilitates more critical review through information gained.

Innovation-Related Breadth and Depth of Expertise and Novelty Preferences

A goal of the study is to understand whether heterogeneity in expertise structure potentially negates the documented biases surrounding ideas of various levels of novelty. To evaluate, I fit variations of the following specification:

$$Impact_{ep} = f_{q1-3}(\beta_0 + \beta_1 Depth_{ep} + \beta_2 Breadth_{ep} + \beta_3 DepthXBreadth_{ep} + (\gamma_p \ or \ X_p) + \gamma_e; \ \epsilon_{ep}) \quad (3.2)$$

where γ_p is a series of proposal-related covariates, including the submitter-citation-based quality proxies, and other variables as previously defined. In this specification f_{q1-3} indicates that the regression is computed over the first, second, and third tertiles of novelty respectively, with the goal of estimating effects conditional on levels of the global or local novelty of the proposal under consideration.

Table 3.7 displays the results, divided by novelty levels along row panels. The first six columns fit regressions according to division along the lines of 'global' proposal novelty while the last three columns estimate only the fully specified fixed effects regressions relative to the 'local' novelty of the proposal to the evaluator. The results indicate that for both the lowest novelty proposals (globally) and the highest novelty proposal (both globally and locally), breadth can negate the critical negative effects of deep expertise as well as the negative effects associated with expertise that is both broad and deep. One standard deviation greater knowledge of MeSH domains (i.e., a standard deviation increase in variety) is weakly estimated in

Table 3.7: Proposal Related Breadth and Depth Conditional on Novelty Tertile

	Novelty, Global ($Novelty_p$)						Novelty, Local ($Novelty_{ep}$)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$Variety_{ep}$		$DivIndex_{ep}$		$RSIndex_{ep}$		$Variety_{ep}$	$DivIndex_{ep}$	$RSIndex_{ep}$
					High Novelty				
$Depth = DepthMean_{ep}$	-0.30	-0.11	-0.63	-0.45*	-0.45	-0.20	0.089	-0.22	0.054
	(0.29)	(0.13)	(0.50)	(0.22)	(0.34)	(0.14)	(0.18)	(0.23)	(0.16)
$Breadth_{ep}$	0.52+	0.19	-0.093	-0.10	0.34	0.079	0.24+	-0.25*	-0.00089
	(0.30)	(0.17)	(0.20)	(0.11)	(0.25)	(0.13)	(0.12)	(0.12)	(0.12)
$Breadth_{ep} \times Depth_{ep}$	-0.42*	-0.22*	-0.24	-0.26*	-0.33	-0.23*	-0.22*	-0.22	-0.27*
	(0.17)	(0.092)	(0.29)	(0.13)	(0.22)	(0.095)	(0.11)	(0.16)	(0.12)
					Medium Novelty				
$Depth = DepthMean_{ep}$	-0.093	-0.087	-0.19	-0.27	-0.15	-0.15	-0.31*	-0.58*	-0.33*
	(0.21)	(0.19)	(0.32)	(0.22)	(0.21)	(0.18)	(0.12)	(0.24)	(0.13)
$Breadth_{ep}$	0.17	0.12	-0.097	-0.20+	0.28+	0.092	-0.13	-0.18	-0.095
	(0.16)	(0.14)	(0.15)	(0.12)	(0.16)	(0.12)	(0.19)	(0.12)	(0.12)
$Breadth_{ep} \times Depth_{ep}$	-0.21*	-0.22*	-0.016	-0.076	-0.22	-0.19	-0.19	-0.20	-0.10
	(0.11)	(0.093)	(0.21)	(0.18)	(0.19)	(0.15)	(0.12)	(0.16)	(0.10)
					Low Novelty				
$Depth = DepthMean_{ep}$	0.050	0.037	-0.26	-0.23	-0.20	-0.046	-0.0011	-0.084	-0.032
	(0.19)	(0.069)	(0.39)	(0.16)	(0.13)	(0.080)	(0.072)	(0.14)	(0.078)
$Breadth_{ep}$	0.62*	0.0020	-0.16	-0.17+	0.21	-0.15	-0.26	-0.12	-0.084
	(0.24)	(0.13)	(0.21)	(0.098)	(0.22)	(0.11)	(0.23)	(0.10)	(0.14)
$Breadth_{ep} \times Depth_{ep}$	-0.47	-0.17	-0.071	-0.21	-0.087	-0.071	-0.053	-0.060	-0.050
	(0.33)	(0.13)	(0.38)	(0.14)	(0.21)	(0.096)	(0.12)	(0.11)	(0.089)
Prop. Controls	Yes	No	Yes	No	Yes	No	No	No	No
Evaluator FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Proposal FE	No	Yes	No	Yes	No	Yes	Yes	Yes	Yes

Notes: The table displays regression of impact scores on both breadth and depth measures conditional on tertiles of novelty (high, medium, low). Proposal controls leveraged include sum of submitter citation counts, max citation count to any one submitter paper, indicator variables for whether the proposal contains a background section or structuring elements, the character length of the proposal, and the number of figures and number of references in the proposal. Similar results in magnitude, significance, and sign are obtained if specified as an ordered logistic model (unreported). Constants excluded from output. Robust standard errors in parenthesis. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

the proposal covariates specification (column 1) to increase perceived impact of proposals by just over a half a point for high novelty proposals and 0.62 points for low novelty proposals conditional on mean depth. Further, this increase for high novelty proposals negates the effects of just over a one standard deviation increase in greater depth. When constrained to local novelty, similar results of lesser magnitude are identified for the impact of expertise variety on perceived impact. However, when breadth is invested in the dimensions of distance or disparity, negative point estimates return, although they are not always significant.

3.4.2 Outside Expertise and Perceived Impact

Up to this point, analysis has been confined to considering the influence of an evaluator's innovation-relevant expertise on their perception of the innovation's perceived value. This aligns with prior studies of intellectual expertise that primarily have employed cosine similarity as the univariate measure of expertise (e.g. Boudreau et al. 2016; Criscuolo et al. 2016), and which mathematically eliminates outside expertise as a source of relevant variation. However, naivete and marginality have been shown to be important to discovering high-performance solutions (Jeppesen and Lakhani, 2010), suggesting that less-related or 'outside' expertise may drive expert evaluation.

Figure 3.2 plots impact scores against two measures of outside expertise, the mean depth of an evaluator's outside expertise ($depthMean_{e \notin p}$) and the mean distance from the set of proposal MeSH terms to the 5 most frequent MeSH terms in the evaluator's outside expertise (the outside 'Knowledge Cluster'). While the subplots of the figure with unmodified scores suggest a negative trend (subplots a and c), the figures involving normalized impact scores suggest a neutral or positive trend (subplots b and d).

One complication of measuring outside expertise via aggregate statistics is the occurrence of near perfect-collinearity between evaluator-level mean depth of expertise $DepthMean_e$ and evaluators' outside expertise (see Table 3.3). Given this, I focus on estimating the effects of distance to an evaluator's largest outside expertise knowledge cluster as well as the effects of the structure of that knowledge cluster. Specifically, I fit:

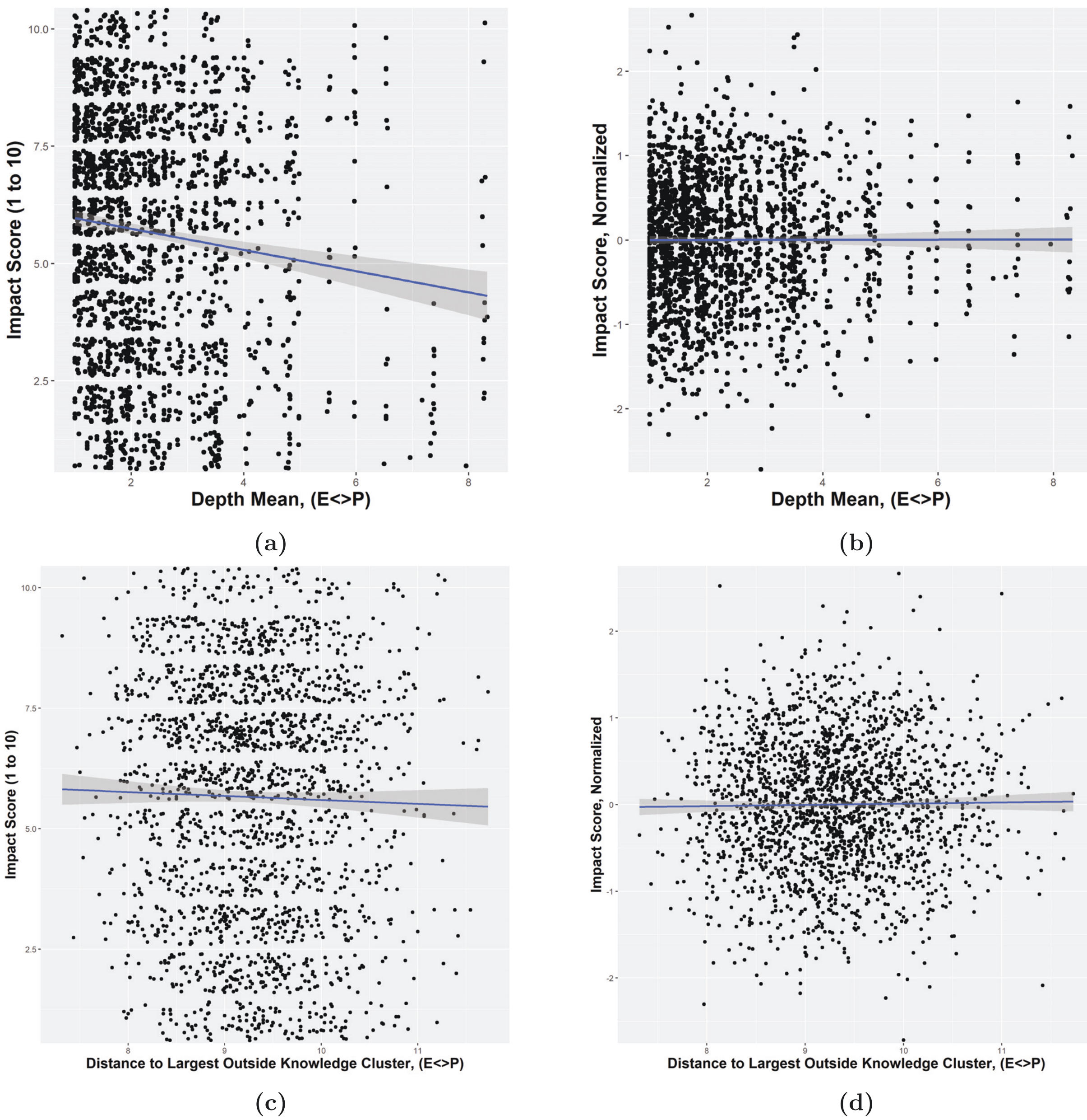


Figure 3.2: Impact Scores and Outside Expertise

Notes: The four figures plot evaluator's ratings of the perceived impact of proposals against the mean depth of an evaluator's largest outside knowledge cluster ($DepthMean_{e \notin p}$, subplots a and b) and the mean distance between the proposal knowledge and the evaluator's largest outside knowledge cluster ($DistClust_{ep}$), where the cluster is defined as the most frequent five MeSH in their outside expertise. E<>P indicates $e \notin p$. The figures are accompanied by ordinary-least squares trend lines of y = f(x), accompanied by 95% confidence intervals in grey. The vertical axis of subplots (a) and (c) is impact score, jittered for visualization purposes. The vertical axis of subplots (b) and (d) is the impact score first standardized by evaluator and then demeaned by proposal (mean = 0; sd = 0.75; min = -2.7; max = 2.66).

$$Impact_{ep} = f(\beta_0 + \beta_1 DistToClust_{e \notin p} + \beta_2 DistInClust_{e \notin p} + \beta_3 DepthMeanClust_{e \notin p} + \delta_1 Breadth_{ep} + \delta_2 Depth_{ep} + \gamma_p + \gamma_e;\ \epsilon_{ep}) \quad (3.3)$$

where $DistToClust_{e \notin p}$ is the mean distance between the MeSH terms of the proposal and those of the outside knowledge cluster, $DistInClust_{e \notin p}$ is defined as the mean distance among the terms that comprise the cluster and is a measure of cluster cohesiveness (with cohesiveness decreasing and disparity increasing as the measure is larger), and $DepthMeanClust_{e \notin p}$ is the mean depth of expertise within the cluster, with other variables as previously defined.[11]

Table 3.8 shows the results of the regressions, which suggest that a one standard deviation increase in the distance between a proposal and an evaluator's largest expertise knowledge cluster $DistToClus_{e \notin p}$ is associated with an increase in the perceived impact of the proposal by 0.37 points. Likewise, a standard deviation increase in the depth of the evaluator's outside knowledge cluster is associated with a large 2.59 point increase (equivalent to a single standard deviation increase) in the evaluator's perceptions of the proposals' potential impact. These effects persist even when holding fixed the evaluator's breadth and depth of expertise in the MeSH term topics covered by the proposal, indicating a large and significant relationship between outside knowledge and the scores an evaluator assigns.

One concern may be that the inclusion of $DepthMeanClust_{e \notin p}$ confounds the regression due to collinearity with other measures of evaluator accumulation of expertise, such as number of publications or seniority, despite the presence of evaluator-level fixed effects. In unreported regressions, I consider the same specification but first normalize $DistToClust_{e \notin p}$ by the number of evaluator publications. Effect sizes increase to 3.194 points and 3.198 points per standard deviation increase relative to Table 3.8 columns 3 and 4, respectively.

[11] As the outside knowledge cluster is of fixed variety by definition, I leverage a measure of disparity to proxy for variation in the breadth of evaluators' outside knowledge clusters

Table 3.8: Impact, Breadth, Depth, and Distance to Evaluator's Largest Knowledge Cluster

	(1)	(2)	(3)	(4)
$DistToClust_{e\notin p}$	0.38*	0.38*	0.38*	0.37*
	(0.16)	(0.16)	(0.16)	(0.16)
$DistInClust_{e\notin p}$			-0.26	-0.26
			(0.29)	(0.29)
$DistToClust_{e\notin p}\times$ $DistInClust_{e\notin p}$				0.018
				(0.070)
$DepthMeanClust_{e\notin p}$			2.55+	2.59*
			(1.33)	(1.31)
$DistToClust_{e\notin p}\times$ $DepthMeanClust_{e\notin p}$				0.053
				(0.059)
cons	6.35***	6.31***	7.68***	7.71***
	(0.79)	(0.79)	(1.09)	(1.09)
$Breadth_{ep}$ & $Depth_{ep}$	No	Yes	Yes	Yes
Evaluator FE	Yes	Yes	Yes	Yes
Proposal FE	Yes	Yes	Yes	Yes
N. Obs	2,055	2,055	2,055	2,055
Adj. R	0.47	0.47	0.47	0.47

Notes: The table displays regression of impact scores on characteristics of evaluator expertise. Similar results in magnitude, significance, and sign are obtained if specified as an ordered logistic model (unreported). Robust standard errors in parenthesis. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

3.4.3 Outside Expertise and Novelty Preferences

The final analysis considers whether outside inventor expertise is associated with differential novelty preferences among evaluators. To analyze, I re-estimate Equation 3.3 on data split across novelty tertiles, with results in Table 3.9.

As with breadth in context of proposal-related knowledge domains, the table illustrates that evaluators who exhibit breadth and depth in external knowledge express greater preference for both high novelty and low novelty grant proposals when compared against evaluators without those qualities. Among proposals with high global novelty, a single standard deviation increase in both the distance to an evaluator's largest knowledge cluster and the distance among the topics within that cluster is associated with a 0.3 point increase in estimated proposal impact. Among proposals which exhibit high local novelty, one standard deviation above mean greater depth in the outside knowledge cluster is associated with assigning an additional 4.79 points to a proposal on average. Similar effects are identified in the case of proposals that exhibit low global novelty.

3.5 Discussion

This study focuses on the relationship between evaluators' structure of knowledge expertise and their consequent perceptions of potential value in scientific innovations they review. It achieves a series of findings. Study analyses indicate that greater depth and breadth of innovation-related expertise is associated with more critical review of innovations on average. Holding fixed evaluators' proposal-related knowledge, outside knowledge is shown to substantially increase evaluators' preferences for innovations. When considering the well documented penalty against high and low novelty ideas, the results show that breadth of knowledge, when combined with depth of related knowledge or when involving investment in outside knowledge domains, moderates and even overcomes biases against high - and in some cases, low - novelty. Evaluators whose innovation-relevant expertise is both deep and broad, as compared with just deep, will perceive greater potential in highly novel innovations on average.

These findings hold significant managerial implications, particularly for expert-based evaluation settings when organizational goals dictate selecting for or against highly novel innovations. Example settings include peer review in science where conservatism may be problematic (Azoulay et al., 2011, 2019; Lee et al., 2013), as

Table 3.9: Novelty, Breadth, Depth, and Distance to Evaluator's Largest Knowledge Cluster

	Novelty, Global ($Novelty_p$)			Novelty, Local ($Novelty_{ep}$)		
	L	M	H	L	M	H
	(1)	(2)	(3)	(4)	(5)	(6)
$DistToClust_{e \notin p}$	0.39	0.27	0.30	0.74*	0.62*	-0.072
	(0.31)	(0.33)	(0.31)	(0.29)	(0.32)	(0.35)
$DistInClust_{e \notin p}$	-0.27	-0.90	0.025	0.26	-1.09+	-0.54
	(0.45)	(0.60)	(0.57)	(0.50)	(0.58)	(0.49)
$DistToClust_{e \notin p} \times$	-0.086	-0.11	0.30*	-0.026	0.058	0.11
$DistInClust_{e \notin p}$	(0.15)	(0.11)	(0.14)	(0.14)	(0.18)	(0.12)
$DepthMeanClust_{e \notin p}$	4.68*	2.67	2.69	-0.11	2.41	4.79+
	(1.92)	(1.98)	(2.36)	(2.14)	(1.60)	(2.63)
$DistToClust_{e \notin p} \times$	0.11	-0.092	0.096	0.060	-0.014	0.17
$DepthMeanClust_{e \notin p}$	(0.12)	(0.078)	(0.19)	(0.16)	(0.11)	(0.11)
cons	8.90***	6.19***	7.91***	5.73***	6.44***	9.17***
	(1.77)	(1.56)	(1.76)	(1.62)	(1.30)	(2.15)
$Breadth_{ep}$ & $Depth_{ep}$	Yes	Yes	Yes	Yes	Yes	Yes
Evaluator FE	Yes	Yes	Yes	Yes	Yes	Yes
Proposal FE	Yes	Yes	Yes	Yes	Yes	Yes
N. Obs	691	686	678	729	681	645
Adj. R	0.45	0.48	0.50	0.47	0.45	0.47

Notes: The table displays regression of impact scores on characteristics of the evaluator's largest knowledge cluster, with the sample divided into novelty tertiles. Similar results in magnitude, significance, and sign are obtained if specified as an ordered logistic model (unreported). Robust standard errors in parenthesis. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

well as innovation review settings in industry where novelty is preferred (e.g., venture capital). These findings suggest that managers seeking to select for highly novel innovations should recruit two sorts of evaluators - those with great diversity of expertise but not necessarily expert in the innovation under consideration and those who possess comprehensive (broad as well as deep) knowledge relevant to the innovation under consideration (and possibly comprehensive knowledge of an unrelated, distant, cohesive topic). Evaluators who possess deep knowledge in only a slice of a highly novel innovation under review, in contrast, are demonstrated to be substantially more critical of such innovations and averse towards them, and it is not clear this critical review conveys additional benefits or insight in the evaluative process.

These findings also contribute to the scholarly literature. This study represents a core contribution to a growing literature on the management of novelty-evaluation processes in science and technology (Boudreau et al., 2016; Ferguson and Carnabuci, 2017; Wang et al., 2017; Criscuolo et al., 2016; Li, 2017) by delineating with greater nuance how the structure of expertise influences evaluators' preferences for novel innovations. In addition, these same findings contribute to the literature on human capital and the direction of inventive activity (Agrawal et al., 2016; Azoulay et al., 2010, 2019; Bateman and Hess, 2015; Borjas and Doran, 2015; Boudreau et al., 2016; Foster et al., 2015; Jones, 2009, 2010; Jones and Weinberg, 2011) by measuring with nuance the depth and breadth of evaluators' expertise and then by demonstrating how aspects of human capital investments along these dimensions drive the selection of levels of novelty among innovations. It is apparent that evaluative systems will under-select highly novel ideas when interdisciplinarity is discouraged (Foster et al., 2015; Leahey, 2017) and diverse evaluators under-recruited in favor of evaluators with specialized subject matter expertise that may be only partially pertinent to knowledge relationships explored in the innovation under review. This finding corroborates the oft-heard refrain from participants in the institutional processes of science that the culture of peer review is overly conservative and disincentivizes the production and investigation of highly novel, high-risk science (Azoulay et al., 2011; Charlton, 2009; Kolata, 2009; Petsko, 2012; Walsh, 2013). However, it also provides insight into how the penalty against highly novel research activity might be overcome through the selection of evaluators who possess greater diversity of intellectual expertise, a finding which contributes to understanding how specialization and generalization influence the direction of scientific discovery. Prior empirical research, in contrast, has primarily focused on the influence of human capital differences on the invention and discovery process (Bateman and Hess, 2015; Teodoridis, 2018) as opposed to the evaluation of innovations.

The study suffered from some limitations. First, its findings relied on citation controls as an imperfect measure of the quality of novel scientific ideas. Second, several of the results identified were only suggestive, and find weak statistical significance (i.e., 80th percentile). Finally, despite granular measurement of the components of intellectual expertise, these results explained surprisingly little of the variation observed (on the order of 1% to 4% without control covariates) in evaluators' perceptions of innovative value. These magnitudes are comparable with those obtained in other studies of the evaluation of novel science and innovations (Boudreau et al., 2016; Li, 2017; Criscuolo et al., 2016), but they beg the question of what *drives* the remaining substantially large variation after covariates are included.

These points suggest opportunities for future research. A larger scale experiment designed in the same manner as the one from which this study drew its data may be beneficial to estimate the effects more precisely or to identify the causes that drove the unexplained variation in evaluations observed here. An experiment implementing a novel design or novel measure that more accurately controls for the influence of innovation quality would constitute a significant contribution to the literature. Additionally, any follow-on research that fully identifies the role that the shape of unrelated expertise plays in evaluation would be beneficial, especially that revealing theoretical mechanisms. With few exceptions, current theory has largely ignored the role of outside, unrelated information on evaluation processes (Hong and Page, 2009). Finally, actually implementing the managerial policy interventions that emerged from this research in an experimental setting would produce useful insights, as would identifying whether such interventions result in predicted shifts in the novelty of organizations' selected innovation portfolios.

Chapter 4

Conclusion

In this dissertation, I explore how management of human capital-related factors causally impact firms' innovation outcomes. Specifically, I investigate, in sequence, (1) how access to diverse human capital impacts firms' innovation and financial performance, (2) how policy-related barriers to human capital mobility drive the globalization of innovations and MNEs' within-country innovation activities, and (3) how innovation evaluation and funding management processes are impacted by the structure of evaluators' knowledge-based expertise.

The results of the first chapter show that innovator human capital is a high-value asset to the firm, that inventor value depends on heterogeneity of inventor human capital as well as on industry context, and that losses in firm equity due to lost inventor human capital are difficult to recoup in the short-run. The average value of inventor's human capital to the firm is estimated to amount to approximately $400 thousand to $1.2 million in 2012 USD for the sample considered, and a back-of-the-envelope calculation based on this estimate suggests that the value of the mean inventor in the larger population of inventors is closer to $104 thousand to $313 thousand in 2012 USD. As with patent asset values, the results show that the distribution of human capital value is highly skewed. The results additionally explore whether inventors' value to firms varies heterogeneously by human capital types or by industry. Unsurprisingly, superstar inventors are estimated to be particularly valuable for firms, with asset values estimated at approximately $4 million in 2012 USD. Inventors with teaming experience are also found to have positive asset value, but this asset value is estimated to be less than that of the average inventor and is indistinguishable when considering standard errors. Additionally, the study identifies that certain industries exhibit positive asset values for inventors, while other industries appear not to. In particular, inventors appear to convey positive asset value to firms when they are involved with firms related to industrial machinery and computing, electronic components and equipment, and chemicals.

The contributions of the study are three-fold. First, I report novel estimates of the asset value of innovative human capital and introduce a novel approach to estimating its asset values. These results contribute to previous literature that estimates the market value of innovations via analyses of firm financial returns (Kogan et al., 2017; Austin, 1993; Pakes, 2018; Hall et al., 2005; Nicholas, 2008). Importantly, while these prior assessments quantify the value to firms of the patents as an intellectual property asset, the present study is the first to produce causal, market value estimates of innovator human capital. Second, I demonstrate that innovative human capital varies in value according to human capital type or skills. Previous studies on human capital and productivity identified positive benefits to various human capital types, such as general-use (Becker, 1975), firm-specific (Topel, 1991), and team-specific (Jaravel et al., 2018) human capital. However, directly placing an asset value on such human capital heterogeneity has been difficult, and the present results provide initial evidence on the value of such heterogeneity. Third, the results contribute evidence in support of the knowledge-based view of the firm and related literature that suggests that human capital and human resource management are essential for firms' competitive advantage (Noe et al., 2017). While previous empirical evidence largely relies on correlational and survey-oriented results (e.g. Østergaard et al. 2011; Haneda and Ito 2018), this study demonstrates the causal link between firm reliance on differing types of innovator human capital and competitive advantage and long-run success.

Future studies may explore whether the value of innovative human capital varies among small firms, private firms, or start-ups. Other future research can also address the extent to which the value of differential skills received via training, such as teaming capabilities or leadership training, moderates the value of human capital to firms. In this respect, one prediction could be that training particular skills complements certain types of innovator knowledge or disciplines or industries (e.g., reliance on science might be particularly valuable for biochemists in pharmaceutical innovation). Other work may analyze the value of inventors' networks external to the firm, as access to information networks and knowledge brokerage is predictive of innovation (Burt, 2001, 2004; Hargadon and Sutton, 1997). This opens a possibility to explore how more or less expansive networks of inventors influence their value in augmenting the firm's absorptive capacity and positively increase the firm's acquisition of novel knowledge. Finally, in the chapter, I find significant costs associated with human capital loss, suggesting possible management techniques to reduce those costs, such as recruitment of redundant human capital or diversity in firms' research portfolios. In further research, it would be useful, for both scholars and practitioners alike, to establish to what extent these strategies can alleviate firms' dependence on human capital.

The purpose of the second chapter (from co-authored work) is to investigate the interrelationship between shifting barriers or costs to human capital migration and MNE subsidiaries engagement with globalized knowledge production. We do so through investigating whether and to what extent MNEs' subsidiary-level investments in innovation change following reforms to migration policy that ease barriers to long-term, business-related immigration to a country. We find that long-term oriented pro-business reforms to migration policy significantly drive MNE investment within a country, increasing the annual GCPs produced therein by between approximately 0.5% and 5% on average, depending on specification. we additionally investigate whether the magnitude of the marginal effects of reforms depends on MNEs' total patenting volume and find that MNEs with above mean patenting volume are responsible for the large majority of increases in patenting outcomes, producing 2 to 5 times as many patents, global collaborative patents, and domestic patents as their below-mean peers. We then consider whether the positive effects identified are driven primarily by long-term migrant inventors (those who we observe permanently move within the patenting data) or whether the increases in patenting activity originate with other inventors. The results present strong evidence that these 'non-permanent migrant' inventors drive the majority of increases in patenting, suggesting that there exists significant spillovers from the pro-long-term business migration reforms onto non-long-term inventors, and that these spillovers are greater in magnitude than those produced among inventors who do engage in long-term migration.

Given these findings, the study produces three contributions. First, via demonstrating the responsiveness of MNEs to changes in the barriers to migration, particularly for global collaborative patenting, the study shows that skilled migration is a key input to the production of global innovations among the modern MNE, and that it causally depends on the context of high-skill human capital mobility policy. Second, the results reinforce the importance of 'absorptive capacity' as a concept that represents the role of the subsidiary within the MNE. This is particularly true among large MNEs, which are shown to significantly benefit relative to small MNEs from easing the barriers to high-skilled business-related migration. This provides support for the knowledge-based view of the MNE, namely, that MNEs and their subsidiaries exist due to their ability to manage knowledge transfers in the face of international barriers to market transactions and the moderating role of subsidiaries in receiving and accumulating knowledge (e.g., Kogut and Zander 1992, 1996; Caves 1971; Cohen and Levinthal 1990). Finally, we begin to shed light on the importance of invention spillovers due to shifting barriers to migration within MNEs, particularly originating with short-term migrants or from migrants to non-migrants. Our results suggest a potentially large role of such spillovers from migration policy for MNE innovation.

Some key questions remain unanswered. First, whether shifting barriers to migration impact patenting primarily on the margin of the non-migrant (e.g. through learning from migrants and through collaborations) or on the margin of the short-term or cyclical migrant, remains an open question. As cyclical and short-term migration is increasingly common and recognized as key to business processes (Gmur and de Sola, 2013; Kerr et al., 2016), it would be helpful for policy makers, managers, and scholars alike to identify upon which margin the reforms primarily induce novel invention among MNEs. Second, as we rely on specifications involving fixed effects at the MNE-year level, we are unable to identify changes attributable to the MNEs' aggregate production of inventions. Determining whether shifting barriers to migration impacts the overall level of innovation is a worthy challenge that could produce significant efficiencies in R&D allocation if known.

In the third chapter, I focused on the relationship between evaluators' structure of knowledge expertise and their consequent perceptions of potential value in scientific innovations they review. It achieves a series of findings. Study analyses indicate that greater depth and breadth of innovation-related expertise is associated with more critical review of innovations on average. Holding fixed evaluators' proposal-related knowledge, outside knowledge is shown to substantially increase evaluators' preferences for innovations. When considering the well documented penalty against high and low novelty ideas, the results show that breadth of knowledge, when combined with depth of related knowledge or when involving investment in outside knowledge domains, moderates and even overcomes biases against high - and in some cases, low - novelty. Evaluators whose innovation-relevant expertise is both deep and broad, as compared with just deep, will perceive greater potential in highly novel innovations on average. These findings hold significant managerial implications, particularly for expert-based evaluation settings when organizational goals dictate selecting for or against highly novel innovations. They suggest that managers seeking to select for highly novel innovations should recruit two sorts of evaluators - those with great diversity of expertise in domains external to the innovations under consideration and those who possess comprehensive (broad as well as deep) knowledge relevant to the innovation under consideration (and possibly comprehensive knowledge of an unrelated, distant, cohesive topic). Evaluators who possess deep knowledge in only a slice of a highly novel innovation under review, in contrast, are demonstrated to be substantially more critical of such innovations and averse towards them, and it is not clear this critical review conveys additional benefits or insight in the evaluative process.

These findings also represent a substantial contribution to the scholarly literature. This study represents a core contribution to a growing literature on the management of novelty-evaluation processes in science and technology (Boudreau et al., 2016; Ferguson and Carnabuci, 2017; Wang et al., 2017; Criscuolo et al., 2016; Li, 2017) by delineating with greater nuance how the structure of evaluator's expertise influences evaluators' preferences for novel innovations. In addition, these same findings contribute to the literature on human capital and the direction of inventive activity (Agrawal et al., 2016; Azoulay et al., 2010, 2019; Bateman and Hess, 2015; Borjas and Doran, 2015; Boudreau et al., 2016; Foster et al., 2015; Jones, 2009, 2010; Jones and Weinberg, 2011) by measuring with nuance the depth and breadth of evaluators" expertise and then by demonstrating how aspects of human capital investments along these dimensions drive the selection of levels of novelty among innovations.

These points suggest opportunities for future research. A larger scale experiment designed in the same manner as the one from which this study drew its data may be beneficial to estimate the effects more precisely or to identify the causes that drove the unexplained variation in evaluations observed here. An experiment implementing a novel design or novel measure that more accurately controls for the influence of innovation quality would constitute a significant contribution to the literature. Additionally, any follow-on research that fully identifies the role that the shape of unrelated expertise plays in evaluation would be beneficial, especially that revealing theoretical mechanisms. With few exceptions, current theory has largely ignored the role of outside, unrelated information on evaluation processes (Hong and Page, 2009). Finally, actually implementing the managerial policy interventions that emerged from this research in an experimental setting would be beneficial, as would identifying whether such interventions result in predicted shifts in the novelty of organizations' selected innovation portfolios. An additional contribution would be to directly measure the extent to which such shifts towards increased selection of more novel innovations resulted in benefits to societal welfare via greater knowledge accumulation.

Overall, the dissertation provides evidence for the knowledge-based view of the firm (Kogut and Zander, 1992, 1996), and provides nuance with regards to the factors that managers may strategically influence to implement firms' innovation strategies. It additionally produces insights for policy makers regarding how the structure of human capital, both within markets and among individuals, influence the innovation and value propositions of firms, and, consequently, economic growth (Romer, 1990). However, the research herein begins to uncover and describe the nature of economic dependence on innovation-related human capital processes, and can serve as a launching point for future work on uncovering and delineating such relationships.

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Wang, J., Veugelers, R. and Stephan, P. (2017), 'Bias against novelty in science: A cautionary tale for users of bibliometric indicators', *Research Policy* **46**(8), 1416–1436.

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Weitzman, M. (1998), 'Recombinant Growth', *Quarterly Journal of Economics* **113**(2), 331–360.

Wuchty, S., Jones, B. F. and Uzzi, B. (2007), 'The Increasing Dominance of Teams in Production of Knowledge', *Science* **316**(5827), 1036–1039.

Appendix A

Appendix to Chapter 1

A.1 Identifying Deceased and Incapacitated Inventors

The goal of the study is to examine the impact of the unexpected deaths of inventors on firm performance outcomes. In order to do so, it is necessary to construct a sample of deceased inventors. To identify deceased inventors, I draw on data from three sources: Google Patent Search, the United States Patent and Trademark Office (USPTO) PatentsView pre-formatted data, and the USPTO's raw bulk XML patent data.[1]

A.1.1 Legal Requirements to Identify Deceased or Incapacitated Inventors on Patents and Patent Applications

Inventor death events are measured directly from patent data, and there exist strict legal requirements to report inventor deaths as part of the patent application and grant processes. Patent law and regulations require that all inventors who participated in the establishment of a patent's claims are listed on the application for the patent. Under United States Code 35 (U.S.C.) 115, further detailed in the Code of Federal Rules 37 CFR 1.64 and the Manual of Patent Examining Procedures (MPEP) 602.01, each inventor of a patent is required to submit an inventor's oath or declaration listing all joint inventors as well as attesting to

[1] Google Patent Search is accessible at `https://patents.google.com/advanced`, the PatentsView data is available at `http://www.patentsview.org/download/` and the USPTO Bulk Data repository files are available at `https://bulkdata.uspto.gov/`. The version of the PatentsView data leveraged in the study is the November 27, 2018 data update.

their own inventorship. Further, under 35 U.S.C. 117 and MPEP 409, inventors are required to apply jointly for a patent, and provisions are outlined for joint application in the event of unavailability of an inventor. Specifically, MPEP 409 requires that

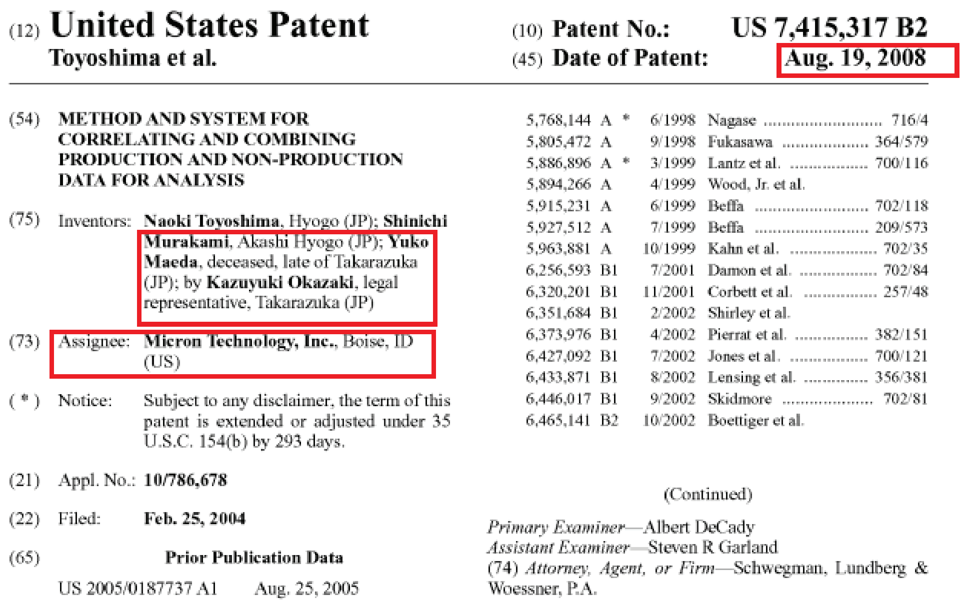
> "If a joint inventor refuses to join in an application for patent or cannot be found or reached after diligent effort, the application may be made by the other inventor on behalf of himself and the omitted inventor." (MPEP 409.02 and MPEP 409.03)

In the event that inventors are deceased or otherwise incapacitated, legal representatives are empowered to apply for a patent in the inventor's stead (MPEP 409). The result is that inventors and legal representatives often apply for patents while reporting deceased inventors, and in patent bibliographic texts inventors who have died are often listed as deceased. Inventor deaths can therefore be identified in patent grants and applications from the presence of inventors with a 'deceased' status and/or via the presence of a legal representatives and/or heirs.

A.1.2 Identifying Deceased or Incapacitated Inventor Signals

Conditional on the submission of an application for a deceased or incapacitated inventors' patent rights, patent-related publications display that an inventor is deceased. This occurs in potentially two ways. First, the inventor is identified on the application with a label in the name field indicating that they are deceased. Second, the legal representative of the inventor and their title (e.g., legal representative, heir, administrator, executor of estate, etc.) are listed as inventor-applicants for the patent. Depending on the timing of death and the scope of the final patent, these records of deceased status may appear on published patent applications (only publicly available since November 29, 2000), on published patent grants, or on both documents.[2]

[2]The legal definition of inventorship in the United States requires an inventor to contribute to the conception of an invention. From MPEP 2137.01,"The definition for inventorship can be simply stated: "The threshold question in determining inventorship is who conceived the invention. Unless a person contributes to the conception of the invention, he is not an inventor. ... Insofar as defining an inventor is concerned, reduction to practice, per se, is irrelevant [except for simultaneous conception and reduction to practice, Fiers v. Revel, 984 F.2d 1164, 1168, 25 USPQ2d 1601, 1604-05 (Fed. Cir. 1993)]. One must contribute to the conception to be an inventor." In re Hardee, 223 USPQ 1122, 1123 (Comm'r Pat. 1984)." Patent examiners discern this threshold at the claim level. As a result, when a claim is rejected or invalidated, an inventor may be removed from subsequent patent application filings and resulting publications as they are no longer considered an inventor on the patent. The consequence is that an inventor may be listed as deceased on a patent application but their inventorship may not be recorded on the actual patent. Further, patent applications were largely not systematically published in the United States until after implementation of the America Invents Act, see `https://www.uspto.gov/web/offices/pac/mpep/s1120.html`, accessed August 28, 2019.



(12) **United States Patent**
Toyoshima et al.

(10) **Patent No.: US 7,415,317 B2**
(45) **Date of Patent: Aug. 19, 2008**

(54) **METHOD AND SYSTEM FOR CORRELATING AND COMBINING PRODUCTION AND NON-PRODUCTION DATA FOR ANALYSIS**

(75) Inventors: **Naoki Toyoshima**, Hyogo (JP); **Shinichi Murakami**, Akashi Hyogo (JP); **Yuko Maeda**, deceased, late of Takarazuka (JP); by **Kazuyuki Okazaki**, legal representative, Takarazuka (JP)

(73) Assignee: **Micron Technology, Inc.**, Boise, ID (US)

(*) Notice: Subject to any disclaimer, the term of this patent is extended or adjusted under 35 U.S.C. 154(b) by 293 days.

(21) Appl. No.: **10/786,678**

(22) Filed: **Feb. 25, 2004**

(65) **Prior Publication Data**

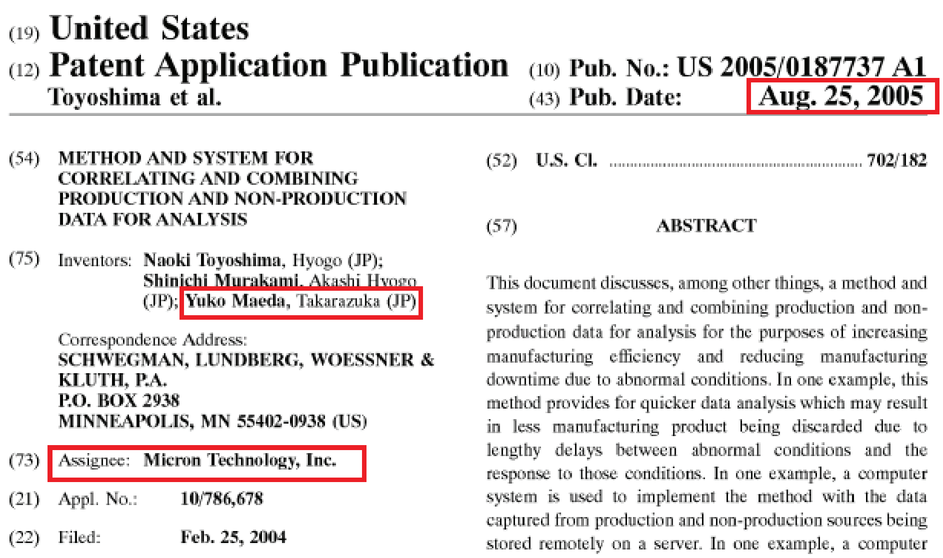
US 2005/0187737 A1 Aug. 25, 2005

5,768,144 A *	6/1998	Nagase		716/4
5,805,472 A	9/1998	Fukasawa		364/579
5,886,896 A *	3/1999	Lantz et al.		700/116
5,894,266 A	4/1999	Wood, Jr. et al.		
5,915,231 A	6/1999	Beffa		702/118
5,927,512 A	7/1999	Beffa		209/573
5,963,881 A	10/1999	Kahn et al.		702/35
6,256,593 B1	7/2001	Damon et al.		702/84
6,320,201 B1	11/2001	Corbett et al.		257/48
6,351,684 B1	2/2002	Shirley et al.		
6,373,976 B1	4/2002	Pierrat et al.		382/151
6,427,092 B1	7/2002	Jones et al.		700/121
6,433,871 B1	8/2002	Lensing et al.		356/381
6,446,017 B1	9/2002	Skidmore		702/81
6,465,141 B2	10/2002	Boettiger et al.		

(Continued)

Primary Examiner—Albert DeCady
Assistant Examiner—Steven R Garland
(74) *Attorney, Agent, or Firm*—Schwegman, Lundberg & Woessner, P.A.

(a) Patent Grant Announcing a Deceased Inventor



(19) **United States**
(12) **Patent Application Publication**
Toyoshima et al.

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(54) **METHOD AND SYSTEM FOR CORRELATING AND COMBINING PRODUCTION AND NON-PRODUCTION DATA FOR ANALYSIS**

(75) Inventors: **Naoki Toyoshima**, Hyogo (JP); **Shinichi Murakami**, Akashi Hyogo (JP); **Yuko Maeda**, Takarazuka (JP)

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(73) Assignee: **Micron Technology, Inc.**

(21) Appl. No.: **10/786,678**

(22) Filed: **Feb. 25, 2004**

(52) **U.S. Cl.** **702/182**

(57) **ABSTRACT**

This document discusses, among other things, a method and system for correlating and combining production and non-production data for analysis for the purposes of increasing manufacturing efficiency and reducing manufacturing downtime due to abnormal conditions. In one example, this method provides for quicker data analysis which may result in less manufacturing product being discarded due to lengthy delays between abnormal conditions and the response to those conditions. In one example, a computer system is used to implement the method with the data captured from production and non-production sources being stored remotely on a server. In one example, a computer

(b) Publication Patent Application Prior to Inventor Death

Figure A.1: Example Patent Records Announcing Inventor Death

Notes: The figure presents an example of patent records announcing the death of an inventor. Subfigure (a) displays the bibliographic front-page text for patent #US7,415,317B2, which was granted and published on Aug 19, 2008. The patent records the death of inventor Yuko Maeda. Subfigure (b) displays the patent application corresponding to the patent, published on Aug. 25, 2005. Yuko Maeda is not identified as 'deceased' in the patent application, indicating that this is an instance where the patent grant announces the death of the inventor.

Figure A.1 provides an example of patent grant and application bibliographic pages where the inventor almost certainly passed away during the application process. As can be seen in Subfigure (a), the patent, granted and published August 19th 2008, lists Yuko Maeda as a deceased inventor on the patent application. Additionally, a legal representative who files for the corresponding inventorship rights, Kazuyuki Okazaki, is identified in the inventor list. The corresponding patent application publication, published on August 25th 2005, lists Yuko as an inventor without a deceased label. In Subfigure (b), we observe the application corresponding to the published grant. Here, Yuko Maeda remains alive. However, in some instances, patents are applied for on behalf of deceased inventors.

In the current study, this patent-application pair would be identified as an instance where an inventor's death is signaled at the point of grant and well after the technical aspects of a patent are established in a prior published application, but not as an instance in which the deceased signal of the grant is 'preempted' by the publication of the application for patent. From comparing this patent with all of Yuko Maeda's other patents, it is additionally clear that this is the first signal of Yuko Maeda's deceased status. The deceased status is therefore considered novel information at the point of patent publication.

Among other key information, the bibliographic text reveals that the patent's intellectual property rights were assigned to Micron Technology, Inc. in Boise, Idaho. From this, it is inferred that Yuko was employed by Micron Technology, Inc at the time of death. As a result, Micron Technology, Inc. is treated as impacted by an inventor death signal as of the patents' publication date.

A.1.3 Constructing a Sample of Deceased Inventors

To collect a complete sample of deceased inventors, I analyzed bibliographic information and metadata of publicly available USPTO patent grant records for the years 1976-2018 (approximately 6.8 million publications) and patent application records for the years 2001–2018 (approximately 8 million publications). In doing so, I identified a sample of 7,516 deceased inventors.

To identify deceased inventors in patent grants, I searched patent records indexed in the following three data sources: Google's Patent Search, USPTO's PatentsView files, and the bulk raw patent XML data provided by the USPTO. First, I used Google Patent Search to search the 'inventor name' fields on all USPTO granted patents for the years 1976-2018 for key terms suggesting that an inventor is listed as deceased or incapacitated. Second, I additionally searched several bibliographic fields within the USPTO

PatentsView project raw inventor data files using fuzzy string-matching techniques. Third, as both USPTO and Google Patent Search were found to have OCR-based text recognition errors as well as errors in the patent data where 'deceased' status was entered in incorrect bibliographic fields, I additionally employed a customized XML-parsing and fuzzy string-matching script to search the raw USPTO Bulk Patent Grant XML files for the years 2001 - 2018 to identify deceased inventors.

Finally, I also identified deceased inventors from published patent applications. After the enactment of the America Invents Act, the USPTO started publishing all patent applications filed on or after November 29, 2000 with an 18-month lag on publication.[3] Therefore, inventors may be identified as deceased when a patent application is published prior to a grant. To separate out these instances, so as to identify all announcements and dates where the deceased status of an inventor was novel information, I downloaded, parsed, and fuzzy string matched (via a custom R script) all patent application records available on the USPTO Bulk Database website.

Identifying deceased inventors took the form of a four-step process. First, deceased inventors were identified in the USPTO PatentsViews data, indexing patents published from 1976 to 2018. Leveraging 'rawinventor.csv', a file indexing raw inventor data on granted patents, inventor name and address fields were scanned using fuzzy string-matching techniques to identify inventors who were labeled as deceased or incapacitated. After review of patent records and the MPEP policies for recording deceased or incapacitated inventors, the terms 'deceased' and 'incapacitated' were searched for, allowing for minor misspellings and transpositions. The results were reviewed manually for accuracy, incorrect retrievals removed (e.g., the last name 'Debease'), and corresponding patent inventors were marked as deceased.

Second, the advanced search feature in Google Patents was leveraged to search the author fields of all USPTO patent publications from 1976 to 2018 for authors with 'deceased' or 'incapacitated' in their names. The results were downloaded and reviewed, and the corresponding inventor-patent records were marked as deceased.

Third, bibliographic front-page XML files for (1) all patent grants and (2) all application publications from 2001 to 2018 were retrieved from the USPTO Bulk Data Products website.[4] A program was written

[3] See this USPTO announcement: `https://www.uspto.gov/about-us/news-updates/uspto-will-begin-publishing-patent-applications`, last accessed 12-1-2019.

[4] 2001 is the earliest point at which the USPTO first publishes standardized XML-format files as opposed to raw text files.

to parse and process these XMLs into usable data. As part of the parsing script, the program searched all name and 'address book' fields to identify deceased inventors. Additionally, the script searched for and parsed keywords identifying legal representatives involved in the patent. During the period of 2000 to August 2009, USPTO XML files explicitly included tags that identified both (1) the deceased status of inventors, and (2) whether and for which inventor a legal representative applied for patent rights. Finally, the program recorded application filing date, application publication date, and patent grant and publication date information for all patent records identified to have a deceased inventor.

After collection, the three lists of deceased inventor records were harmonized with the patent and application data indexed in the USPTO PatentsView database. Fuzzy string-matching on names and matching of patent and application numbers was leveraged to associate deceased inventors to their corresponding patents as well as patent date and timing data. Manual review and examination of patents and patent applications was leveraged to resolve discrepancies in the event of matching conflicts across lists.

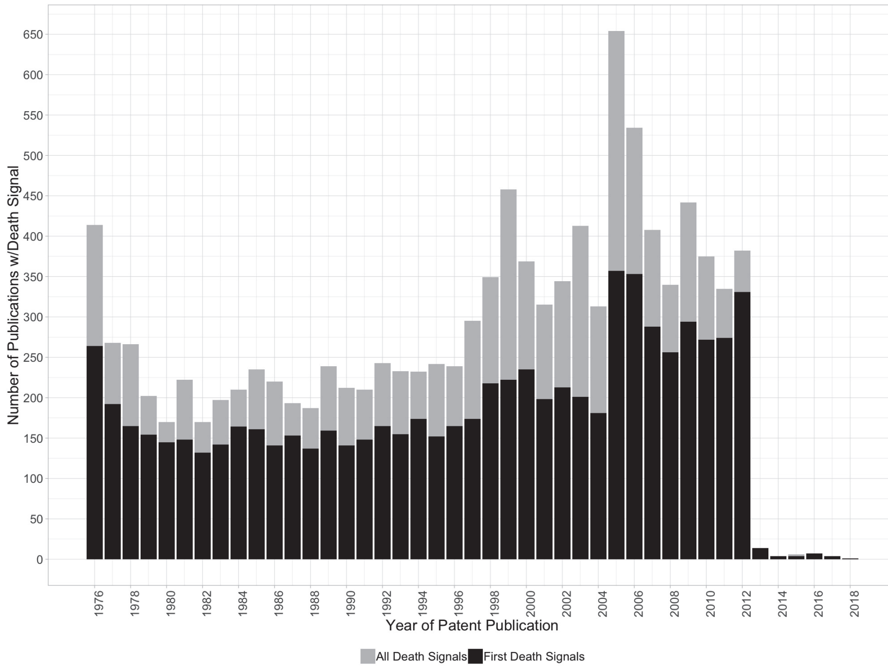
Once the deceased inventor-patent records were identified, PatentsView's disambiguated inventor IDs were used to match patents to each deceased inventor. In addition to recording patents where the inventor is listed as deceased, for each inventor I identify a 'First Death Signal', the first instance where the inventor is signaled publicly as deceased and matched this to the date of the first such publication.

Figure A.2 displays the frequency of measured patent-related publications which signal an inventor death over time (Subfigure a) as well as the frequency of measured inventor deaths over time (Subfigure b). Both figures exhibit rightward censoring post-2012, which emerged from changes in patent office policy on record keeping for deceased inventors - as of December 4th, 2012, the patent office removed from its raw XML files the field used to track deceased inventors and has not yet established a new public system for tracking deceased inventors in raw patent publication data (confirmed via email with USPTO on 8-30-19). As a result, death announcements drop off significantly as inventor deaths must be explicitly recorded in the inventor 'name' or 'address' fields of the patent records in order to be observed.

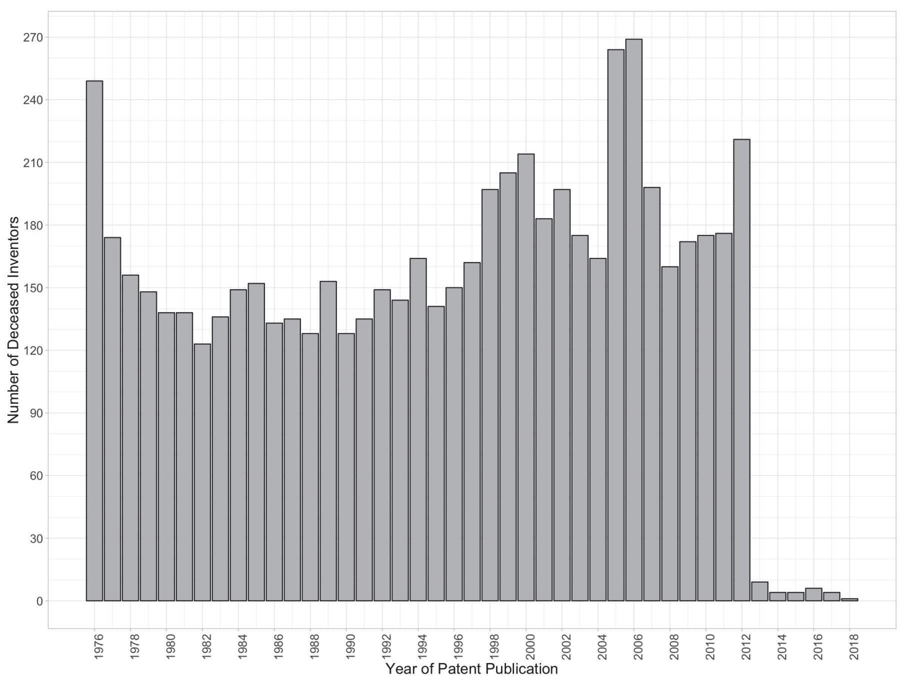
A.1.4 Adjustments to Deceased Inventor Sample

Various adjustments are made to the sample of deceased inventors and their matched patents to ensure that the deaths analyzed correspond to exogenous variation in actual inventor patent portfolios.

Table A.1, Panel A displays the count of unique inventors identified conditional on these restrictions



(a) Death Signals on Published Patent Records Over Time



(b) Deceased Inventors Over Time

Figure A.2: Frequency of Inventor Deaths and Death Announcements Over Time

Notes: The figure displays the frequency of inventor death announcements recorded in patent records over time. Subfigure (a) displays annual counts of patent death announcements identified in patent grant or patent application publications by year. Black bars index the first announcement of death for a given inventor. Grey bars index all death announcements present in patent records. Subfigure (b) displays counts of inventor deaths by year.

Table A.1: Counts of Identified Deceased Inventors and Death Announcement Publications

			Comparison W/	
Signal Type	Count	Percent	Hong (2019)	Jaravel et. al (2018)
Panel A: Deceased Inventors				
Deceased Inventors	$7,516$	100.00%	6,854	
w/Career Age ≤ 30	$7,309$	97.25%	5,681	
& w/any firm-matched patents	$3,095$	41.18%		4,924
& w/firm-matched utility patents before death announcement	900	11.97%		
& w/grants ≤ 6 years post	787	10.47%		
& not preempted in app.	686	9.13%		
w/Career Age ≤ 15	$6,026$	80.18%		
& w/any firm-matched patents	$2,276$	30.28%		
& w/firm-matched utility patents before death announcement	607	8.08%		
& w/grants ≤ 6 years post	548	7.29%		
& not preempted in app.	494	6.58%		
Panel B: Death Announcements				
Published Docs w/Death Signal	$11,530$	100.00%		
Deceased Application	$3,199$	27.75%		
Deceased Patents	$8,840$	76.67%		
Deceased on App., Not on Pat.	$2,690$	23.33%		
Deceased on Pat., Not on App.	$8,338$	72.32%		
Deceased on App. and on Pat.	509	4.41%		
Years Covered:	1976 - 2018		1976 - 2013	1976 - 2012

Notes: The table displays information about the frequency of identified deceased inventors and the patent records signaling their deaths. Panel A displays the count of unique inventors identified conditional on these restrictions and compares the sample sizes against two other known studies of inventor deaths (Jaravel et al., 2018; Hong, 2019) while Panel B displays information on the number of patent records identified which signal inventor deaths.

and compares the sample sizes against two other known studies of inventor deaths (Jaravel et al., 2018; Hong, 2019) while Panel B displays information on the number of patent records identified which signal inventor deaths. The following four restrictions are applied: (1) Prior to analysis, inventors are restricted to those who died with an inferred career age (based on first patent application year to year of death) of either 30 years or less or 15 years or less (for robustness checks). The inventors are then limited to only those (2) with firm-matched utility patents before and at the point of their death announcements (allowing for a within-inventor comparison of patent values), (3) without patent grants greater than 6 years post-death, to exclude mistaken inventor identification in the USPTO PatentsView automated disambiguation of inventors, and (4) with patent grants announcing inventor deaths that are not 'preempted' by a similar announcement on a published application. All together, for the main analysis this leaves a remaining 686 deceased inventors who are studied from the larger sample of 7,516 inventors (a 9% sample).

The inventor sample identified holds up well when compared against other studies of inventor deaths under similar restrictions. Where Hong (2019) identifies 6,854 deceased inventors of which 5,681 have inferred career ages of less than or equal to 30 years, the current study identifies 7,516 and 7,309 inventors, respectively. When compared with Jaravel et al. (2018), the current study matches roughly two thousand fewer inventors to firms. However, Jaravel et al. (2018) benefit from the ability to match inventors leveraging social security data and firm-employer identification numbers. Despite lacking this information, the current study matches 41% of deceased inventors to firms.

A.1.5 Potential Measurement Error and Incentives to Record Inventor Deaths

There exists some potential for measurement error in this identification approach. Somewhat substantial variation exists in the frequency of deceased inventors over time, with a particularly pronounced drop-off in recording after 2012 (see Figure A.2) and, in-practice, inventor deaths are primarily reported first under an 'honor system' approach, with correction or invalidation of inventorship occurring primarily when legal disputes arise. Given this, estimates outlined in the study may be biased if unmeasured inventor deaths occur among firms which are included as 'control' observations in analyses that don't compare within-inventor.

Despite this, such measurement error is unlikely to bias the direction of the effects identified, and only potentially results in underestimation of the magnitude of effects. This is due to two reasons. First, inventor deaths or incapacity, and the sudden loss of human capital, is expected to impose a cost on the firm and its innovation and performance outcomes. Under the assumptions that unobserved inventor deaths are less frequent among control observations and their negative impacts are generally lesser in aggregate than those of the measured inventor deaths, the impact on the estimates produced would be to only reduce the negative magnitude of effects. As positive impacts of inventor loss are not measured in the study - and firms have incentives to separate from such inventors - the non-within-inventor estimates produced are at-most lower bounds on the actual effects of inventor death news on market valuation.

The second reason unobserved inventor deaths are unlikely to cause measurement error is that strong incentives exist to ensure that deceased inventors are recorded. In the event that invention disputes arise, the process for correcting inventorship records historically requires costly coordination across inventors and assignees (Gattari, 2005). Incorrect inventorship recording and resultant disputes can also lead to the invalidation of a patent grant in court. As noted in Konski and Wu (2015, p. 2),

> "Incorrectly identifying inventors can be grounds to invalidate the patent (see Jamesbury Corp. v. United States (518 F.2d 1384, 1395) (Ct. Cl. 1975)3 and C.R. Bard, Inc. v. M3 Systems, Inc. (157 F.3d 1340, 1353) (Fed. Cir. 1998)),4 and omitting an inventor can render a patent unenforceable (Frank's Casing Crew & Rental Tools, Inc. v. PMR Technologies, Ltd. (292 F.3d 1363, 1376) (Fed. Cir. 2002)). Moreover, to bring a patent infringement action, all inventors must be included as plaintiffs, and if a court finds that an inventor has been omitted, the omitted inventor must join as a plaintiff for the litigation to proceed (Ethicon, Inc. v. U.S. Surgical Corp. (135 F.3d 1456, 1465–1466) (Fed. Cir. 1998))."

These potential costs are significant enough that intellectual property law firms inform and advertise regarding the law and their services with respect to inventorship disputes[5], inventorship correction[6], and filing applications when an inventor is deceased.[7]

[5] See, for example, https://www.nutter.com/ip-law-bulletin/its-never-too-late-to-file-an-inventorship-dispute, accessed August 29, 2019.

[6] See, for example, https://www.finnegan.com/en/insights/aia-breathes-life-into-inventorship-correction-in-pto.html, https://www.fenwick.com/FenwickDocuments/Correct_Inventorship.pdf, accessed August 29, 2019.

[7] See, for example, https://www.mmwvlaw.com/filing-assignment-oathdeclaration-deceased-inventor/, accessed August 29, 2019.

A.1.6 Evaluating Exogeneity of Identified Inventor Deaths

This section describes the results of two robustness checks undertaken to evaluate whether the identified inventor deaths and their signals of death represent sudden, unexpected deaths that would have caused exogenous variation on the market in the form of unanticipated news events. The first test is a search for obituaries and news regarding a sample of deceased inventors. The second test is an evaluation of eventually deceased inventors' patent production in the years prior to the inventors' deaths.

Obituary and News Search

To evaluate whether inventor deaths would have been common information prior to patent grants, I conducted an obituary and news search to identify public information about inventors that was released contemporaneous to their deaths. To do so, I randomly sampled a set of 70 of the deceased inventors for who a patent was granted with a deceased status at inferred career ages of 30 years or less and who did not receive patent grants more than six years after their death. The sample was designed to over-represent superstar inventors (19 of the 70 inventors sampled) as well as internet-era inventors (24 of the 70 inventors sampled had inferred dates of death in the year 2000 or later).

For each inventor name sampled, a digital search for obituaries and related news was conducted. First, obituary indexing websites, specifically findagrave.com and Legacy.com, were searched for the inventor's name. Both websites track historic as well as current news about deceased individuals and allow users to submit such news for indexing. Second, a wide web search was conducted on Google.com using the name of the inventor plus key terms including 'obituary', 'death', the locations reported for the inventor on their patents, and the name of the inventor's likely employers (determined by company assignees associated with the inventor's patents).

Of this sample, death information was identifiable for 13 inventors (19%), however, not all sources identified were contemporaneous. Only seven inventors (10%) had sources of news at the local level - funeral home website obituaries, obituaries in local newspapers, obituaries in industry, regional, or national news - which might have been identifiable by anyone tracking the inventor specifically. Additionally, contemporaneous news at an industry, regional, or national level - the sort of news which might have been readily accessible to market traders and potentially influenced trade decisions - was only found for three of the

Table A.2: Obituary News Search Results

Name	Est. Death	Actual Death	Superstar	News Type	News Date	Confirm Unex.	Local Obit.	News Ind.	News Reg.
Max Mengeringhausen	1991-10-15	4/13/1988	0	Wikipedia		0	0	0	0
John W. Von Holdt	2000-08-08	7/15/1998	1	Industry News; Regional News	7/19/1998; 7/27/1998	0	0	1	1
Vincent N. Kahwaty	2000-03-14	6/2/1995	0	Genealogy Website		1	0	0	0
Francis L. Zrostlik	2003-05-06	4/12/2000	0	Industry News; Memorialization Website	4/13/2000	0	0	1	0
Lawrence B. O'Brien	1994-06-28	12/13/1991	0	Gravestone Photo		0	0	0	0
Markus B. Thorgeirsson	1987-03-24	12/24/1984	0	Invention Memorialization Website		0	0	0	0
Fred D. Waldhauer	1996-06-04	3/4/1993	1	Wikipedia; Local Obituary		0	1	0	0
Richard J. Grable	2004-02-17	8/13/2001	0	Local Obituary	8/16/2001	1	1	0	0
Charles E. Molnar	1999-08-10	12/13/1996	0	Local Obituary	1/16/1997	1	1	0	0
John A. Simpson	1994-04-05	10/26/1991	0	Gravestone Photo		0	0	0	0
Roy H. Steinberg	2000-05-23	7/26/1997	0	Local Obituary; National News	8/2/1997; 8/10/1997	0	1	0	1
Hakon Westermarck	2001-03-20	11/27/1995	0	Wikipedia; Geneology		0	0	0	0
Donald E. Hudson	2009-07-21	9/20/2005	0	Funeral Home Obit.		0	0	0	0

Notes: The table displays metadata about identified news and obituary related information from a search for obituary news conducted on a set of 70 inventors. The column 'Est. Death' conveys the estimated date of death for the inventor based on patent grants signaling the inventor is deceased, whereas 'Actual Death' reflects the identified date of death based on news found. 'News Type' is a list of news and information source types identified. 'News date' provides the corresponding dates of publication, if they were found and contemporaneous to the death. 'Confirm Unex.' is a binary variable indicating whether news was able to confirm an individual died unexpectedly, 'Local Obit' indexes whether an obituary was found in a local source of news while the last two columns indicate whether news was found in an industry-related news source ('News Ind.') or in a regional or larger news source ('News Reg').

inventors (4.3%), one who is identified in the data as a superstar.

The search revealed two additionally reassuring factors. First, the search was able to produce information demonstrating that three of the inventors did face unexpected deaths. Given that most results included limited information on the inventors and their deaths, this is interpreted as evidence that at least some positive selection on unexpected deaths is occurring. Second, the search revealed that the main freely available obituary indexing website, Legacy.com and affiliated pages, did not begin to track obituaries widely until the 2003 and after. Overall, the results provide reassurance that financial market participants would have been unlikely to find news of the vast majority of inventor deaths outside of directly examining patent grants.

Exogenous Shock to Inventor Patent Production

A second test of whether the inventor deaths index unexpected variation is to evaluate whether inventor-based outputs face discrete shocks at the point of death. Figure A.3 displays the means and 95% confidence intervals for the number of patent grants in event-time relative to death for all inventors in the 30-year unexpected death signal category that did not receive patent grants more than six years after their death. The figure shows that patent grants remain consistent in the years prior to an inventor's death (with production averaging roughly 2 patent grants per year, a healthy career), but suddenly fall in the year of the inventor's death (to about 1.3 patents). This sudden drop in patent production relative to a healthy average production level suggests that the effect of inventor deaths in innovation markets is sudden and significant. This result provides reassurance that financial markets likely would not identify inventor deaths in advance of patent

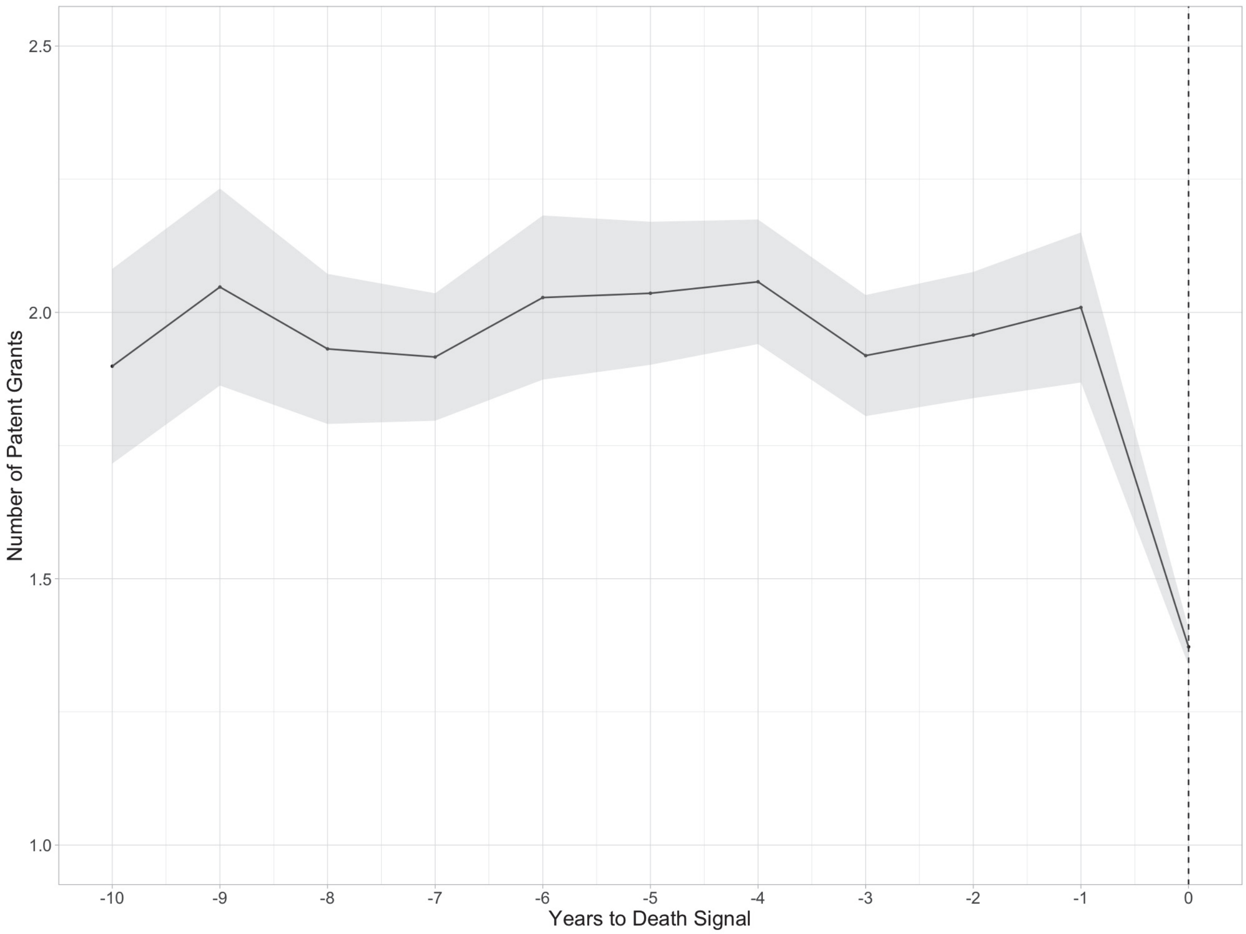


Figure A.3: Patent Grants Over Time Relative to First Announcement of Inventor Death

Notes: This figure displays the path of patent grants over time relative to the first announcement of inventor deaths. Inventors sustain a consistent, average production of about two patents per year in the years preceding a notice of death, with production dropping subsequently in the year of the notice. Mean production does not drop to zero as many inventors are recorded on patent applications which are granted in the years following the inventor's death.

grants announcing such deaths without other information explicitly identifying the death.

A.2 Harmonizing Patent-Firm Linkage Records

The study requires connecting inventors and their patents to the firms to which intellectual property rights are assigned. While patents are frequently assigned to organizations, and these assignees are listed on the patent records, connecting these assignment records to firms faces two difficulties. First, the assignee fields listed on patents often include variations of common firm names, without listing the standardized firm names identified in datasets indexing financial performance (e.g., Standard & Poor's Compustat, the

Center for Research on Security Prices - CRSP - data). For example, IBM may be alternatively listed as International Business Machines, IBM, IBM Corp, and International Business Machines Corp, among other names. Second assignee fields include errors and misspellings that result in individual records that are close in textual distance (e.g., General Electric Oohpany vs. General Electric Company).

To overcome these matching difficulties and to generate a consistent set of firm-patent links, I combine data drawn from three data sources. The first two sources (drawn from Kogan et al. 2017 and Autor et al. 2016) are preexisting datasets that link patenting activity to firm-level identifiers. The third source is a dataset linking patent-to-firm identifiers created for the purpose of this study and to update the data on patent-firm linkages to 2018. These data were harmonized to create a consistent linkage between patents and firms. Out of the 6.8 million patents indexed in patents, the final matched set assigns CRSP permno and permco identifiers to 2,316,774 patents (34%) matched to permno and permco identifiers in CRSP and 3,636,255 patents (53%) matched to GVKEY identifiers in Compustat. The data, its construction, and the harmonization process are described below.

A.2.1 Data Sources

Three datasets of pre-existing patent-to-firm matches are leveraged in the disambiguation process. The first dataset, Kogan et al. (2017), links all USPTO patents indexed in Google Patents between the years 1926 - 2010 to CRSP permanent firm number ('permno') identifiers, yielding 1,928,128 patents matched to firms indexed in CRSP.[8] The authors of that study construct the data in three steps. First, they download corresponding patent records in Google Patents and extract from these records information on all assignees listed in the patents. These assignee records were then standardized across patents as text processing was leveraged to generate consistent assignee names in the face of misspellings (e.g., General Electric Oohpany vs. General Electric Company) and misnomers (e.g., General Electric vs. General Electric Company). Finally, the standardized names were then matched to CRSP permanent firm identifiers ('permco') based on the presence of consistent firm identification in the NBER Patent database, and if still unmatched, based on the inverse-word frequency weighted text-similarity to names present in the CRSP database. Additional details on the data construction in Kogan et al. (2017) are available in the online appendix to that paper.

[8] The data are available via Noah Stoffman's website and at `https://kelley.iu.edu/nstoffma/`. Last accessed Sept 9, 2019.

The second dataset, drawn from Autor et al. (2016), matches assignees on all USPTO granted patents between 1975 and March 2013 to publicly held firms in Compustat and connects 2,155,707 patents to firm identifiers in Compustat. To resolve the disambiguation challenges outlined above, the authors of that study leverage a web search-based disambiguation algorithm. They first search the Internet for the assignee name recorded on patents by using Microsoft's Bing.com search engine. From the returned search results, they associate the assignee name with a list of suggested web domains and Wikipedia pages. These website URLs and information embedded in the Wikipedia pages are then used to match the patent assignee to a firm-level identifier in Compustat ('GVKEY') by comparison against Compustat's name and address related information. Additional details on the ADHPS match can be found in the online appendix to Autor et al. (2016).

The third data source leveraged is derived via text analysis and fuzzy string-matching of USPTO patent data to firm names recorded in Compustat. This data was constructed by matching the USPTO PatentsView data (November 27, 2018 version), including standardized and raw assignee names associated with patents and disambiguated assignee IDs, to Standard & Poor's Compustat Dataset Global and North America Daily Fundamentals files (retrieved June, 7, 2019). To do so, I first created a custom R script to standardize firm names for assignees in the PatentsView data as well as the firm names listed in the Compustat files. The custom R script first employs the NBER Patent Project name standardization routines (Hall et al., 2001) and modifies these routines with further standardization efforts. The results of the script produce both exact standardized firm names that standardize across common terms (e.g., Corporation or Corp.), but which retain full name forms, as well as 'stem' names that drop common terms to be used in the matching process. Following this name standardization, matching then occurs between the Compustat firms and the PatentsView assignee names as follows:

1. **Match based on standardized names and retain all exact matches.** First match on PatentsView's standardized organization names from the 'Assignee' file. For remaining unmatched names, then match on the standardized organization names from the 'RawAssignee' file.

2. **Match on organization stem names and location.** First, leveraging stems from the PatentsView 'Assignees' file, match based on exact matches on stem name and state and retain all new matches, then by stem name and city and retain all new matches. Second, repeat matching using the stem

names derived from the PatentsView 'RawAssignee' file.

3. **Match based on approximate string-matching and exact location.** For all standardized names, derive a pair-wise string distance based on normalized Damerau-Levenshtein distance. Within the resulting matches, the top match for each unmatched name is retained as long as it is in the top quintile of match similarity and has the same geography. First complete this process for organization names in the 'Assignee' file, then for remaining unmatched names in the 'RawAssignee' file.

This matching process yielded 1,088,525 matches between patents and Compustat GVKEY firm identifiers.

A.2.2 Harmonizing Patent-Firm Links

Following collection of the three datasets, the indexed patent-to-firm links were harmonized across the three datasets. Harmonization occurred in the following steps:

1. **Convert GVKEYs to CRSP permno and permco combinations.** GVKEYs are converted to permno and permco combinations via the links outlined in the CRSP/Compustat Merged Database (retrieved 6-24-19).

2. **Retain 3-way matches.** In the event of a 3-way match across all files between a patent and a consistent CRSP identifier, retain the match.

3. **Retain 2-way matches.** For unmatched remainder, in the event of agreement between two of the three files, retain the match.

4. **Retain consistent singular matches across patents.** For unmatched remainder, in the event that a firm-patent match is suggested by any file which also matches that of all of the corresponding PatentsView assignee's other matches to firm identifiers, retain that match.

5. **Assign most frequent matches to unmatched patents.** For any patent which has no match suggested, but for which the corresponding PatentsView assignee has a majority firm match, assign the corresponding firm match to the patent.

6. **Repeat Process for Compustat GVKEYs and CRSP permno/permco until convergence.**

This harmonization process yields 2,316,774 matches between patents and CRSP permno/permco identifiers.

A.3 Computational Appendix

This section outlines computational approaches and methodology for (1) calculating asset value contributed by patent grants in the main-effects study, (2) calculating abnormal returns leveraging the capital assets pricing model (CAPM) and Fama-French plus Momentum model (FFM) in the second set of analyses, and (3) calculating technology-cohort-weighted citation indices.

A.3.1 Calculating Asset Value of Patent Grants

Following Kogan et al. (2017), I infer patent value through treating each patent grant publication in the PatentsView-CRSP matched sample as an 'information event' to which the market responds. However, since my sample varies in coverage and in certain patent-to-permno links, I estimate patent values directly in lieu of leveraging the estimates derived in that study.[9]

Based on the matched PatentsView-CRSP data, abnormal returns associated with patent grants can be estimated by leveraging financial event studies. From these abnormal returns that accrue to firm securities after the patent grant events, one can infer an estimate of the dollar value of each patent grant event. Following the conventional practice (e.g., Austin 1993; Kogan et al. 2017), I estimate short-run abnormal returns in the days immediately surrounding patent grant announcements. Specifically, I decompose stock returns as follows:

$$R_{ft} = E[R_{ft}|X_t] + AR_{ft}$$

where R_{ft} is the actual return for firm stock f on day t, $E[R_{ft}|X_t]$ is the expected return for the stock conditioned on market covariate information X_t, and AR_{ft} is the abnormal return attributed to information

[9] While Kogan et al. (2017) index patents from 1926 - 2010, the present study indexes patents from 1976-2018. Due to differences in matched samples, I match 907,607 patent records to CRSP permnos that are not present in the Kogan et al. data. Furthermore, since I harmonize multiple datasets to improve upon prior matching efforts, approximately 1% (or 20,734 records) of the patents present in both patent data file match to different permno identifiers.

signals at or about day t. Computing abnormal returns enables distinguishing the firm-level idiosyncratic component of returns from market-aligned movements in securities prices. To compute abnormal returns, I employ a market-adjustment model where $E[R_{ft}|X_t]$ is proxied for via a value-weighted market returns index, and the difference between observed returns and expected returns is computed.[10]

After calculating abnormal returns on the daily level, I aggregate such returns across a pre-specified event window, accounting for short periods of multi-day adjustment in stock price and purchases. Following Kogan et al. (2017), I focus on a primary estimate of cumulative returns accruing to the firm within a three-day event window following announcement (t=0 to t=2).[11] In computing cumulative returns, I consider both cumulative abnormal returns (CARs) and buy-and-hold abnormal returns (BHARs) across the event window. From abnormal returns, I calculate $CAR_{i,t;t+K}$ for the period t to $t+K$ as the sum of abnormal returns:

$$CAR_{i,t;t+K} = \sum_{t}^{T_K} AR_{i,t+K}$$

where t is the first day of the event window, and K is the length of the event window. Similarly, I compute $BHAR_{i,t;t+K}$ as the product of consecutive abnormal returns:

$$BHAR_{i,t;t+K} = \prod_{t}^{T_K} (1 + AR_{i,t+K})$$

These abnormal returns are then assumed to embed the following two kinds of information: (1) information related to the patent grant events V_j and (2) statistical 'noise' from other news and events surrounding the firm during that period. Abnormal returns to a stock are therefore further decomposed as follows for a

[10]Specifically, I compute abnormal returns as the difference in the firm's daily return (CRSP:RETD) minus the value-weighted market index (CRSP:VWRETD). While this relies on CRSP's non-model derived volume-weighted portfolio, later analyses demonstrate that the negative impacts estimated to be caused by inventor death signals are robust to specification of the market model via more classic means which estimate a market beta, such as the Capital Assets Pricing model or the Fama-French-Carhart model.

[11]This approach does not considerably vary from other studies on the impact of patent grant announcements. For example, Austin (1993) computes returns in a four-day event window encompassing the day prior to a patent grant announcement event to the second day immediately after the announcement event (t=-1 to t=2). However, Kogan et al.'s (2017) event window is empirically supported by stock-level analyses of share turnover surrounding patent events. As my sample of patent events and corresponding securities are very similar to those examined by Kogan et al. (2017), I adopt a similar event window instead of re-conducting analyses of share-turnover surrounding patent events.

given day characterized by patent grants J:

$$AR_{ft} = \frac{\sum V_j}{m_{ft}} + \varepsilon_{ft}$$

where V_j is normalized by the market cap for the firm m_{ft} in order to determine the return to a single share of the security, and ϵ_j is the variation in return attributable to other factors. Combining this model of stock returns with the model of patent asset values yields the following equation:

$$\xi_j + \sum_i^I \omega_{ij} = (1-\overline{\pi})^{-1}\frac{1}{n_j}E[v_j|AR_{ft}]m_{ft}{}^{12}$$

where $E[v_j|AR_{ft}]$ is the expected security-level return to a stock f in day t due to patent grants, n_j is the number of patents granted on a given day of interest t, and other variables are as previously defined.

To complete this estimation, a signal-to-noise equation (Eq. (4) in Kogan et al. 2017) is employed which estimates $E[v_j|AR_{ft}]$ as a function of the relative ratio of variances observed for patent grants and idiosyncratic noise in the market. Assumptions regarding the distribution of stock-level patent-driven returns (v_j) and the noise term (ϵ_j) are derived. As in Kogan et al. (2017), patent grants are represented as an asset with a strictly positive, normally distributed return (e.g., $v_j \sim \mathcal{N}^+(0, \sigma^2_{vft})$, and the noise parameter is distributed symmetrically around mean zero (e.g., $\epsilon_j \sim \mathcal{N}(0, \sigma^2_{\epsilon ft})$. This yields the following 'signal-to-noise' equation:

$$E[v_j|AR_{ft}] = \delta_{ft}AR_{ft} + \sqrt{\delta_{ft}} + \sigma_{\varepsilon ft}\frac{\phi(-\sqrt{\delta_{ft}}\frac{AR_{ft}}{\sigma_{\varepsilon ft}})}{1-\Phi(-\sqrt{\delta_{ft}}\frac{AR_{ft}}{\sigma_{\varepsilon ft}})}$$

where δ_{ft} is the signal-to-noise parameter for v_j relative to ϵ_j,[13] R_{ft} is the aggregated abnormal return across the event window, ϕ represents the standard normal PDF, and Φ is the standard normal CDF. Here, I estimate $\sigma^2_{\epsilon ft}$ non-parametrically as the sum of squared abnormal returns divided by n-1 trading days at

[12]As in Kogan et al. (2017), $(1-\overline{\pi})$ is held static at 0.44 as prior evidence suggests that the unconditional probability of a obtaining a patent grant from a patent application is approximately 56% (Carley et al., 2015). m_{ft}, the market equity capitalization of the firm, is calculated as the product of the price of the firm's stock at close of the most recent trading day times the outstanding shares reported at market open on day t.

[13]Said differently, $\delta_{ft} = \frac{\sigma^2_{vft}}{\sigma^2_{vft}+\sigma^2_{\epsilon ft}}$. Following Kogan et al. (2017), δ_{ft} is held static at the benchmark value of $\hat{\delta}_{ft} = 0.0145$, the value estimated from equation (6) in that paper. To check robustness of results, I re-estimate γ in specifications using equation (6) in Kogan et al. (2017) and find similar core results despite slightly differing values of $\hat{\gamma}$ and $\hat{\sigma}$.

the firm-year level.

A.3.2 CAPM and FFM Event Studies

The second analysis in the study considers the implications of the larger sample of firm-matched deceased patent news signals on the returns faced by firms, and in doing so, allows for a robustness check on the assumptions of the main analysis. While the Kogan et al. (2017) approach imposes the assumption that asset values for patents must remain positive, there is sufficient justification to assume they may not hold in all instances, and that returns due to patents may occasionally deviate in unanticipated ways. For example, should a patent's value not be fully understood prior to grant, and the market remains uninformed of the technical knowledge of the patent (e.g., as in the case of an un-marketed patent originating separately from a skunk-works division of the firm), the realization of a patent may convey novel information about the (possibly misaligned) research portfolio of the firm which could yield negative value to the firm. Similarly, the loss of a costly, but non-productive inventor could convey positive value to the firm as the firm would no longer be contracted to pay that inventor's salary, whereas the loss of an inventive superstar may represent a significant cost to the firm well in excess of the value of the simultaneously received patent asset. Given the potential for these circumstances, I relax the assumption in the second set of analyses to allow that the combined return is normally distributed (e.g., $E[v_j|R_j] \sim \mathcal{N}(0, \sigma^2_{vft} + \sigma^2_{\epsilon ft}))$ and demonstrate that negative asset values of inventors persist in that setting.

In these secondary analyses, abnormal returns are estimated via the Capital-Assets Pricing Model (CAPM or Market Model) and, to demonstrate robustness, via a Fama-French plus Momentum four-factor model following Carhart (1997).

The CAPM model is estimated via the formula:

$$(R_{it} - R_{ft}) = \alpha_i + \beta_i(R_{mt} - R_{ft}) + \epsilon_{it}$$

where R_{it} is firm security i's realized return on day t, R_{ft} is the daily risk-free rate, R_{mt} is the market rate, and ϵ_{it} is a noise parameter assumed normally distributed. Here, the market rate of return is proxied for via the CRSP value-weight market index and the risk-free rate is the 30-day treasury-bill return rate from Ibbotson Associates.

The Fama-French plus Momentum model is computed as follows:

$$R_{it} - R_{ft} = \alpha_i + \beta_{1i}(R_{mt} - R_{ft}) + \beta_{2i} SMB_t + beta_{3i} HML_t + \beta_{4i} MOM_t + \epsilon_{it}$$

where expected returns are further a function of a size premium factor comparing the return on a portfolio of small to large firms (SMB_t), a value premium factor comparing the return on a portfolio of high to low book-to-market value firms (HML_t), and a momentum factor comparing the return on a portfolio of high relative to low performing firms in the prior 2 to 12 months (MOM_t).[14] Other parameters are as specified in the CAPM model.

In analyses, I fit the equations to a pre-estimation window corresponding to 150 to 50 days prior to patenting announcement events [t=-150, t=-50], and then predict the expected returns on the period of the event-window surrounding the patenting event. These predictions are then leveraged in calculating abnormal returns.

A.3.3 Technology Cohort-Weighted Citation Measures

Computing technology-weighted citation indices which aggregate short-run citations is a standard practice to adjust for differential rates of citation within patent cohorts and technology types (Hall et al., 2005). The index leveraged in this study is computed using the Cooperative Patent Classification (CPC) treaty taxonomy that classifies patents according to their technical characteristics. The tech-class weighted citation index is calculated as the sum of 5-year citations accrued to the patent j divided by the mean of patent j's citation over all tech classes at a given taxonomy level h:

$$\frac{C}{\overline{C}_{tw}} = \frac{\sum_{\tau=t}^{\tau+5} Cites_{j,\tau}}{Tech\ Class\ Cites_{j,h}}$$

where τ represents years relative to patent j's grant year t, and $cites_{j,\tau}$ is a count of citations to patent j in year $t+\tau$. From this measure, $Tech\ Class\ Cites_{j,h}$ for patent j and cpc taxonomy level h is computed as:

[14] These Fama French Plus Momentum factor indices are available from Kenneth French's data library, accessible at `https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_developed_daily_mom.html`. Last accessed 8/29/19.

$$Tech\ Class\ Cites_{j,h} = \frac{1}{N_L} \sum_{l}^{L \in j,h} (\sum_{k}^{K \in l,t} \frac{Forward\ Cite\ Index_k}{N_K})$$

where N_L is the number of tech classes at taxonomy level h assigned to patent j, $L \in j, h$ indexes the set of such CPC tech classes, K indexes the set of all patents assigned to tech class l and granted in cohort year t, and N_K is the number of such patents in that set. For calculating the technology-weighted citations, I set $h = 3$, but highly correlated indices are produced when construction occurs across CPC hierarchy levels ($h = 1\ to\ 5$).

A.4 Additional Robustness Checks

A variety of additional robustness checks are run to evaluate the validity of the results in the main paper. For the main analysis, the robustness checks include recomputing the key estimate on the subset of inventors whose career age is 15 years or less at death, computing winsorized estimates of the main effect, and estimating the sensitivity of the results to variation in the event time window examined. For the secondary analysis examining 15-day returns, robustness checks are examined that confirm the absence of anticipation of inventor death news in the 10-day 'runup' window prior to death events, that show that patents with deceased inventors signals at the point of grant do not exhibit abnormal returns in the periods surrounding the application suggesting that such patents are not differentiated at the point of application, and that demonstrate that non-cumulative abnormal returns do not deviate significantly from a zero-return in the periods prior to grants signaling inventor deaths.

A.4.1 Robustness Results for Main Analysis

15-Year Career Age

Table A.3 shows the results of recomputing the estimates in Table 1.3, but constrained to the subset of inventors who have a career age of 15 years or less at the point of their signaled death, holding other sample limitations the same. The table finds that, under such sample restrictions, the mean inventor is worth approximately \$490 thousand to \$573 thousand in 2012 USD, with a 90% confidence interval bound of between \$175 thousand on the low end and \$890 thousand on the high end. These mean point estimates

Table A.3: Difference in Patent Value Moments, Deceased Inventors with 15-year or less Career Age

Within Dimensions	$\overline{V_A} - \overline{V_D}$	$\frac{(\overline{V_A}-\overline{V_D})}{\overline{\xi_A}\times N_d}$	Test Values		
Mean Statistics			*t-p*	t 90% Conf. Int.	
Inventor	4.90	16%	0.01	1.75	8.06
Inventor, CPC1	5.73	18%	0.00	2.66	8.79
Inventor, CPC1, SIC1	5.70	18%	0.00	2.51	8.90
Inventor, CPC1, Firm	4.90	16%	0.01	1.75	8.06
Median Statistics			*MW-p*	MW 90% Conf. Int.	
Inventor	0.54	16%	0.00	0.19	0.55
Inventor, CPC1	0.60	18%	0.00	0.19	0.68
Inventor, CPC1, SIC1	0.50	16%	0.00	0.16	0.62
Inventor, CPC1, Firm	0.58	18%	0.00	0.14	0.58

Notes: The table presents the difference in patent values by patent grant signal type for inventors whose death occurred at an inferred invention career age of 15 years or less. Valuations are computed by constraining inventors and patents to those observations where the inventor is granted patents with both 'alive' and 'deceased' signals and by conducting a 'within inventor' paired comparison, where the mean of an inventor's 'Alive' patent grants is compared against the estimated value awarded at grant to the first patent announcing an inventors' death. The distribution of 'alive-signaling' patents is further constrained to match the 'deceased-signaling' patent in technological-class (CPC1), industry (SIC1) and individual CRSP firm. The column $\overline{V_A}-\overline{V_D}$, is the difference in distribution moments. The column $\frac{\overline{V_A}-\overline{V_D}}{\overline{\xi_A}\times N_d}$ is the estimate of the percent of asset value associated with an inventor's human capital on patents. The last three columns contain (1) the p-values from paired significance tests for difference in moments, and (2) corresponding 90% confidence intervals. Student's t-test for difference in means is indicated by t and MW indicates Mann-Whitney U-test. Sample sizes are as follows for each comparison (where n_i indexes number of inventors and n_p number of patents): Within Inventor $n_i = 494$, $n_p = 3,037$; Within Inventor, CPC1 $n_i = 409$, $n_p = 2,295$; Within Inventor, CPC1, SIC1 $n_i = 391$, $n_p = 2,132$; Within Inventor, CPC1, Firm $n_i = 377$, $n_p = 2,069$.

suggest that the average inventor conveys asset value to the firm worth approximately 16% to 18% of the value of the average patent. Relative to the main results presented in the core of the paper, these findings align in magnitude with those of the discontinuity analysis.

Winsorized Estimates

One concern may be that the main results observed in the paper are driven entirely by outlier patent observations with extreme value, and that the positive asset value assigned to inventors is an artifact of the allocation of outlier patents across the two distributions. To ameliorate this concern, I estimate inventor asset values on estimates of patent value returns winsorized at the 95^{th} percentile among all patent value returns. Table A.4 displays the results from re-estimating Table 1.3 on the winsorized returns for the sample

Table A.4: Difference in Patent Value Moments, Deceased Inventors with 30-year or less Career Age, Winsorized

Within Dimensions	$\overline{V_A} - \overline{V_D}$	$\frac{(\overline{V_A} - \overline{V_D})}{\overline{\xi_A} \times N_d}$	Test Values		
Mean Statistics			*t-p*	t 90% Conf. Int.	
Inventor	1.04	10%	0	0.77	1.31
Inventor, CPC1	1.04	10%	0.00	0.76	1.33
Inventor, CPC1, SIC1	0.94	9%	0.00	0.66	1.22
Inventor, CPC1, Firm	0.95	9%	0.00	0.68	1.21
Median Statistics			*MW-p*	MW 90% Conf. Int.	
Inventor	0.69	19%	0.00	0.22	0.53
Inventor, CPC1	0.71	19%	0.00	0.20	0.57
Inventor, CPC1, SIC1	0.52	16%	0.00	0.15	0.48
Inventor, CPC1, Firm	0.72	19%	0.00	0.18	0.53

Notes: The table presents the difference in winsorized patent values by patent grant signal type for inventors whose death occurred at an inferred invention career age of 15 years or less. Valuations are computed by constraining inventors and patents to those observations where the inventor is granted patents with both 'alive' and 'deceased' signals and by conducting a 'within inventor' paired comparison, where the mean of an inventor's 'Alive' patent grants is compared against the estimated value awarded at grant to the first patent announcing an inventors' death. The distribution of 'alive-signaling' patents is further constrained to match the 'deceased-signaling' patent in technological-class (CPC1), industry (SIC1) and individual CRSP firm. The column $\overline{V_A} - \overline{V_D}$, is the difference in distribution moments. The column $\frac{\overline{V_A} - \overline{V_D}}{\overline{\xi_A} \times N_d}$ is the estimate of the percent of asset value associated with an inventor's human capital on patents. The last three columns contain (1) the p-values from paired significance tests for difference in moments, and (2) corresponding 90% confidence intervals. Student's t-test for difference in means is indicated by t and MW indicates Mann-Whitney U-test. Sample sizes are as follows for each comparison (where n_i indexes number of inventors and n_p number of patents): Within Inventor $n_i = 494$, $n_p = 3,037$; Within Inventor $n_i = 686$, $n_p = 5,531$; Within Inventor, CPC1 $n_i = 582$, $n_p = 3955$; Within Inventor, CPC1, SIC1 $n_i = 551$, $n_p = 3,602$; Within Inventor, CPC1, Firm $n_i = 530$, $n_p = 3,504$.

of inventors with career age of 30 years or fewer at their signaled death. Table A.5 shows the same estimates leveraging the winsorized returns but computed over the sample of inventors with career age of 15 years or less.

The results of these robustness checks is to identify positive, but significantly lesser, mean asset values of inventors. Calculating asset values this way reduces the estimated mean value of human capital to approximately 9% to 10% of the average value of a patent among the deceased inventor sample with career age of 30 years or less, and to approximately 5% to 7% of the average value of a patent among the deceased inventor sample with career age of 15 or less. Given that long-tail values are a characteristic of patents and innovation, and these analyses already control within inventor, firm, and technology class, these estimates are best treated as lower bounds on the possible mean value of inventors as opposed to accurate estimates. That all estimates remain positive despite winsorized returns provides reassurance of the robustness of the estimated asset values in the main results.

Table A.5: Difference in Patent Value Moments, Deceased Inventors with 15-year or less Career Age, Winsorized

Within Dimensions	$\overline{V_A} - \overline{V_D}$	$\frac{(\overline{V_A} - \overline{V_D})}{\overline{\xi_A} \times N_d}$	Test Values		
Mean Statistics			*t-p*	t 90% Conf. Int.	
Inventor	0.52	5%	0.00	0.23	0.82
Inventor, CPC1	0.71	7%	0.00	0.38	1.05
Inventor, CPC1, SIC1	0.62	6%	0.00	0.29	0.95
Inventor, CPC1, Firm	0.52	5%	0.00	0.23	0.82
Median Statistics			*MW-p*	MW 90% Conf. Int.	
Inventor	0.54	16%	0.00	0.08	0.30
Inventor, CPC1	0.54	17%	0.00	0.04	0.28
Inventor, CPC1, SIC1	0.50	16%	0.01	0.02	0.22
Inventor, CPC1, Firm	0.58	18%	0.01	0.01	0.20

Notes: The table presents the difference in winsorized patent values by patent grant signal type for inventors whose death occurred at an inferred invention career age of 15 years or less. Valuations are computed by constraining inventors and patents to those observations where the inventor is granted patents with both 'alive' and 'deceased' signals and by conducting a 'within inventor' paired comparison, where the mean of an inventor's 'Alive' patent grants is compared against the estimated value awarded at grant to the first patent announcing an inventors' death. The distribution of 'alive-signaling' patents is further constrained to match the 'deceased-signaling' patent in technological-class (CPC1), industry (SIC1) and individual CRSP firm. The column $\overline{V_A} - \overline{V_D}$, is the difference in distribution moments. The column $\frac{\overline{V_A} - \overline{V_D}}{\overline{\xi_A} \times N_d}$ is the estimate of the percent of asset value associated with an inventor's human capital on patents. The last three columns contain (1) the p-values from paired significance tests for difference in moments, and (2) corresponding 90% confidence intervals. Student's t-test for difference in means is indicated by t and MW indicates Mann-Whitney U-test. Sample sizes are as follows for each comparison (where n_i indexes number of inventors and n_p number of patents): Within Inventor $n_i = 494$, $n_p = 3,037$; Within Inventor, CPC1 $n_i = 409$, $n_p = 2,295$; Within Inventor, CPC1, SIC1 $n_i = 391$, $n_p = 2,132$; Within Inventor, CPC1, Firm $n_i = 377$, $n_p = 2,069$.

Table A.6: Difference in Patent Value Moments

Time Period	$\overline{V_A} - \overline{V_D}$	$\frac{(\overline{V_A} - \overline{V_D})}{\overline{\xi_A} \times N_d}$	Test Values			
Mean Statistics			*ND*	*t-p*	t 95% Conf. Int.	
t = 0 to 1	17.87	30.42%	0.00	0.00	11.72	24.02
t = 0 to 3	17.86	30.42%	0.00	0.00	11.72	24.00
t = 0 to 5	17.90	30.45%	0.00	0.00	11.76	24.05
Median Statistics			*MM-p*	*MW-p*	MW 95% Conf. Int.	
t = 0 to 1	1.23	25.06%	0.00	0.00	0.36	0.81
t = 0 to 3	1.23	24.97%	0.00	0.00	0.36	0.80
t = 0 to 5	1.22	24.86%	0.00	0.00	0.36	0.80

Notes: The table presents the difference in patent values by whether patents include a death announcement. The first three rows show statistics related to the patent distribution means, while the last three rows show statistics related to the patent distribution medians. The first column, $\overline{V_A} - \overline{V_D}$, is the difference in distribution moments. The second column, $\frac{\overline{V_A} - \overline{V_D}}{\overline{\xi_A} \times N_d}$ is the estimate of the percent of asset value associated with an inventor's human capital on patents (where $N_d = 1.0033$ is the estimated unconditional mean number of deceased inventors on patents in the sample with death announcements). The last two columns contain p-values from significance tests for difference in moments. Student's t-test for difference in means is indicated by t, ND indicates the normalized difference, MM indicates Moody's Median Test, and MW indicates Mann-Whitney U-test.

Robustness to Event Study Time Period

A concern about the main analysis may be that the analysis is sensitive to specification of the time period under which patent returns are calculated. To evaluate, Table A.6 estimates the value of inventor human capital conditional on differing time periods for which patent returns at grant are calculated, with alternative time periods of 2-days, 4-days, and 6-days. The results vary little with respect to the choice of time period, suggesting that the observed differences in returns are persistent throughout the return windows examined.

A.4.2 Robustness Results for CAPM and FFM Event Studies

Patent Death Announcements and Patent Grant Events Are Unanticipated

Table A.7 provides further evidence of the lack of event-anticipation effects for patent grants signaling an inventor death from the sample of 'unexpected' deceased inventors. The table shows CARs in the 10-day window preceding the patent grant as well as in the 15-day event window following the grant. In the 10-day window prior to grant, while firms due accumulate positive CARs, firms do not exhibit significant changes in CARs under either statistical model. As firms accumulate non-significant changes in CARs prior to grant, the market likely does not anticipate either the grant of the patent or the receipt of news regarding losses

Table A.7: Cumulative Abnormal Returns of Patent Grants w/Inventor Death Signals

	Capital Assets Pricing Model			*FFM Model*		
Event Time	Mean CARs (%)	Std. Error	t-stat	Mean CARs (%)	Std. Error	t-stat
Runup Window Estimation						
-10	-0.00	0.04	0.05	-0.01	0.04	0.14
-9	-0.04	0.05	0.82	-0.02	0.05	0.32
-8	-0.03	0.06	0.54	-0.00	0.06	0.01
-7	-0.02	0.07	0.22	0.01	0.07	0.14
-6	0.02	0.08	0.20	0.04	0.08	0.55
-5	0.03	0.09	0.38	0.08	0.09	0.89
-4	0.07	0.10	0.69	0.11	0.10	1.17
-3	0.04	0.10	0.34	0.07	0.10	0.71
-2	0.05	0.11	0.42	0.09	0.11	0.78
-1	0.06	0.12	0.54	0.12	0.12	1.06
Event Window Estimation						
0	-0.01	0.03	0.28	0.00	0.03	0.14
1	-0.10**	0.05	2.19	-0.08*	0.05	1.71
2	-0.11*	0.06	1.77	-0.07	0.06	1.17
3	-0.19***	0.07	2.85	-0.15**	0.07	2.18
4	-0.19**	0.08	2.57	-0.15**	0.08	2.03
5	-0.20**	0.08	2.37	-0.16**	0.08	1.97
6	-0.24***	0.09	2.68	-0.20**	0.09	2.20
7	-0.32***	0.09	3.40	-0.28***	0.09	3.00
8	-0.32***	0.10	3.25	-0.27***	0.10	2.70
9	-0.35***	0.10	3.37	-0.28***	0.10	2.66
10	-0.28**	0.11	2.50	-0.20*	0.11	1.76
11	-0.24**	0.12	2.10	-0.18	0.12	1.51
12	-0.28**	0.12	2.30	-0.22*	0.12	1.77
13	-0.23*	0.12	1.89	-0.17	0.12	1.39
14	-0.25*	0.13	1.94	-0.18	0.13	1.36
15	-0.29**	0.14	2.10	-0.20	0.14	1.45

Notes: The table presents cumulative average returns accrued (CARs) to securities with patent grants announcing inventor deaths. CARs are calculated across two windows, a 'runup' window estimating returns prior to the publication of the patent grant and an 'event' window following the announcement of the patent grant. Results are robust to: (1) whether estimated on the full sample of patents or restricted only to the patents with eventually deceased inventors, and (2) if estimates are computed leveraging buy-and-hold abnormal returns (BHARs). Abnormal returns are computed via (1) the Capital Assets Pricing Model and (2) the Fama-French Plus Momentum model based on a pre-event estimation window indexing the time period [-150, -50], and requiring at least 50 observations per event for the estimation period. The estimation is robust to specifications of different models of returns and calculating abnormal returns via the Market-Adjustment Model (AR = Return - CRSP's Value Weighted Index [VWRETD]). * $p<0.05$, ** $p<0.01$, *** $p<0.001$

to human capital for the firm. However, the negative returns indicated in the days subsequent to the grant reinforce that the market reacts negatively subsequent to signals of inventor death. This provides further evidence of the absence of pre-trend in advance of inventor deaths.

Comparability of Patent Events With and Without Death Announcements

To further ensure that the distribution of patents signaling inventor deaths does not systematically vary from that of the patents without such signals, I next examine whether application returns systematically vary at the point of application for the patents that eventually signal an inventor death. Table A.8 presents the abnormal market returns accruing to securities of firms granted a patent announcing an inventor's death, circa the *application* date for the patent. In the table, the returns do not significantly deviate from a null effect in either period for a prolonged duration, suggesting that applications by eventually deceased inventors go unnoticed by the market. Additionally, the lack of abnormal returns suggests that application events for patents announcing deceased inventors are similar to those of other patenting events.

Absence of Non-Cumulative Abnormal Returns

An additional concern may be that the cumulative nature of returns is masking significant deviation in non-cumulative abnormal returns accrued by the firm in the days preceding patent grants which record an inventor as deceased. Figure A.4 displays the by-day mean of non-cumulative abnormal returns surrounding patent grants which signal an inventor death. The absence of pre-trend in abnormal returns is consistent across (1) both model types (CAPM and FFM) and (2) the patent group under consideration (either the first patent indicating a death or all such patents). However, regardless of variation estimated, negative returns following the patent grant are significantly identified in t=1, 3, and 7, reinforcing that inventor death signals are followed by negative returns to impacted firms.

Table A.8: Cumulative Abnormal Returns of Patent Applications w/Inventor Death Signals

	Capital Assets Pricing Model			*FFM Model*		
Event Time	Mean CARs (%)	Std. Error	t-stat	Mean CARs (%)	Std. Error	t-stat
Runup Window Estimation						
-10	-0.04	0.04	1.16	-0.03	0.04	0.79
-9	-0.08	0.05	1.48	-0.06	0.05	1.28
-8	-0.12*	0.06	1.81	-0.10	0.06	1.62
-7	-0.10	0.07	1.40	-0.10	0.07	1.35
-6	-0.12	0.08	1.45	-0.12	0.08	1.41
-5	-0.13	0.09	1.36	-0.11	0.09	1.25
-4	-0.11	0.10	1.15	-0.10	0.10	0.99
-3	-0.09	0.10	0.89	-0.10	0.10	1.00
-2	-0.06	0.11	0.55	-0.07	0.11	0.60
-1	-0.06	0.11	0.51	-0.05	0.12	0.42
Event Window Estimation						
0	-0.05	0.04	1.27	-0.05	0.04	1.20
1	-0.02	0.06	0.38	-0.01	0.05	0.23
2	-0.01	0.07	0.09	0.03	0.07	0.38
3	-0.02	0.08	0.22	0.02	0.07	0.21
4	-0.07	0.08	0.85	-0.05	0.08	0.63
5	0.02	0.09	0.26	0.04	0.09	0.40
6	0.06	0.10	0.61	0.04	0.10	0.45
7	0.09	0.11	0.88	0.09	0.11	0.87
8	-0.02	0.11	0.15	-0.01	0.11	0.10
9	-0.00	0.12	0.03	-0.02	0.12	0.16
10	-0.05	0.12	0.41	-0.06	0.12	0.52
11	0.03	0.13	0.20	-0.01	0.13	0.10
12	0.03	0.14	0.19	-0.02	0.13	0.13
13	0.02	0.14	0.18	-0.02	0.14	0.18
14	0.00	0.14	0.02	-0.05	0.14	0.37
15	0.02	0.15	0.12	-0.04	0.15	0.25

Notes: The table presents cumulative average returns accrued (CARs) to securities surrounding the period of patent application for all applications corresponding to eventual grants that announce inventor deaths. CARs are calculated across two windows, a 'runup' window estimating returns prior to the application for the patent and an 'event' window following the application. Results are robust to: (1) whether estimated on the full sample of patents or restricted only to the patents with eventually deceased inventors, and (2) if estimates are computed leveraging buy-and-hold abnormal returns (BHARs). Abnormal returns are computed via (1) the Capital Assets Pricing Model and (2) the Fama-French Plus Momentum model based on a pre-event estimation window indexing the time period [-150, -50], and requiring at least 50 observations per event for the estimation period. The estimation is robust to specifications of different models of returns and calculating abnormal returns via the Market-Adjustment Model (AR = Return - CRSP's Value Weighted Index [VWRETD])). * p<0.05, ** p<0.01, *** p<0.001

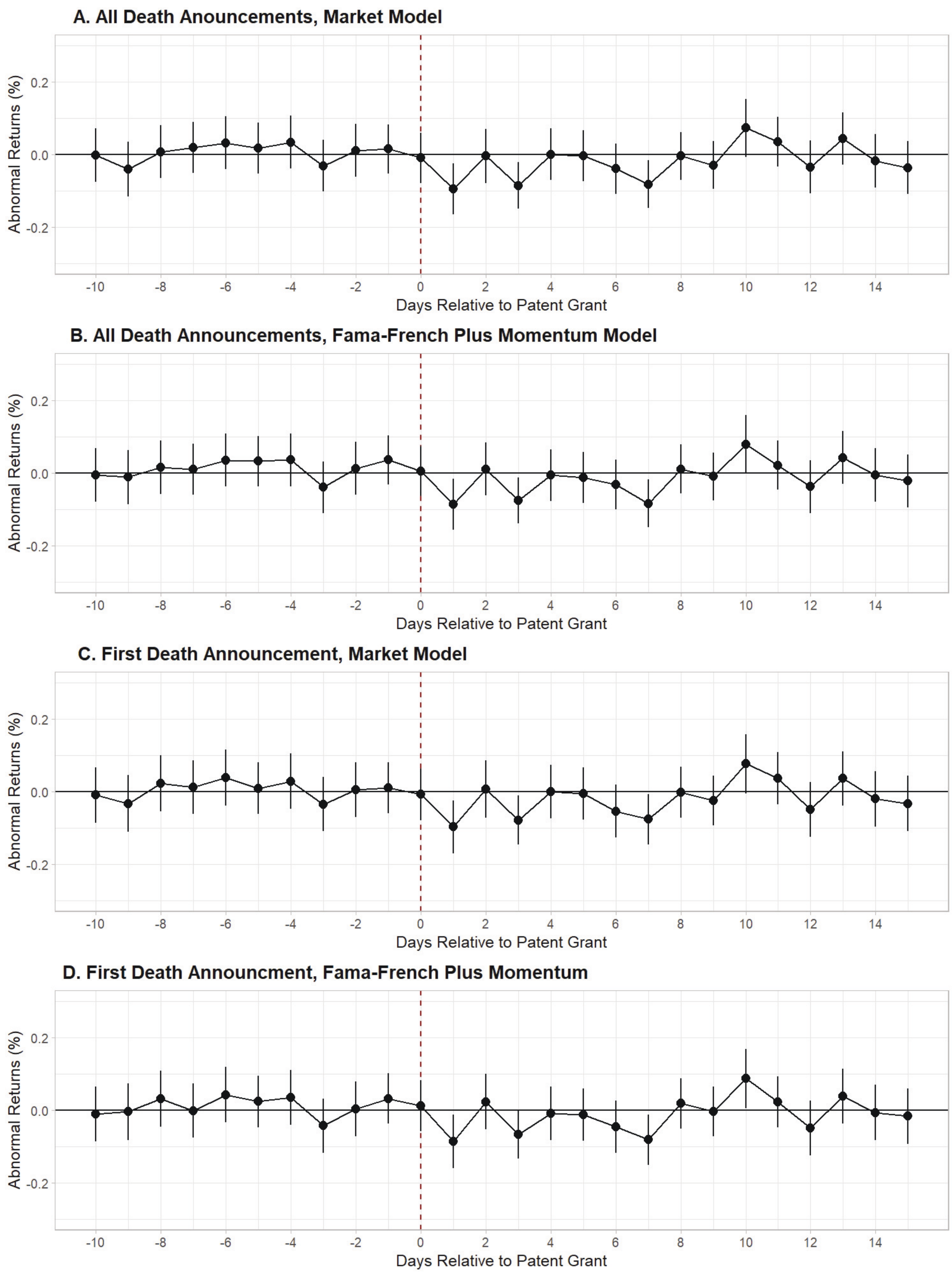


Figure A.4: Abnormal Returns Surrounding Patent Grants Announcing Inventor Deaths

Notes: The figure presents abnormal returns surrounding patent grant events which signal inventor deaths. As noted by the panels, abnormal returns are presented for either all announcements of inventor death or the first announcement of an inventor's death, and abnormal returns are computed leveraging the capital assets pricing model (Market Model) or the Fama-French Plus Momentum model (Fama-French Plus Momentum). The number of events leveraged in computation is as follows by panel: A and B - between 3,644 and 3,638 events depending on time period; C and D - between 3,402 and 3,3396 events depending on time period.

Appendix B

Appendix to Chapter 2

B.1 Reform Data

This appendix focuses on the collection and construction of the database of unilateral reforms to migration policy impacting high-skilled migrants. For the current study, a subset of reforms is examined that impact migration related to long-term business, defined as impacting business-related travel of a year or greater in length or permanent migration. The first subsection provides the list of reforms. The second subsection describes the collection of the larger dataset of reforms. The full dataset of reforms is available upon request from the author.

B.1.1 Study Reforms

For each reform examined in this study, figure B.1 lists the country impacted, the year of implementation, the estimated impacts on migrants, and a brief description of the reform.

Table B.1: Descriptions of Study Reforms

Country	Year	Title	Impacts	Brief Description
Chile	2005	Ratification of "The International Convention on the Protection of the Rights of All Migratory Workers and Their Families"	Increase Rights	Chile ratified the United Nations convention on migrant workers and developed policies to assist in their integration, which increased migrant worker rights. For example, immigrant children could attend school and be treated equally to native students regardless of migratory status, and healthcare access in public hospitals was granted to immigrant children and pregnant women.
China	2004	Decree No. 74	Increase Volume, Increase Rights	The act specified a "Green Card" policy for China which allowed for immigration based on categories, including technical immigration. For technical immigration, migrants need to hold title of associate director/associate professor equivalent or above.
Germany	2005	Migration Act of 2005	Increase Volume, Increase Rights	This act involved a complete overhaul of German migration policy. It amended the Nationality Act and introduced a new Residence Act that simplified and reduced the number of residence titles to two: a temporary residence permit and a permanent settlement permit. The act shifted policy to focus on long-term permanent residency for migrants, in particular for skilled workers, and on integration measures.
Germany	2012	EU Blue Card (Article 19a, German Residence Act)	Increase Volume	Introduced the 'Blue Card' based on European Community Directive (Directive 2009/50/EC) that created a European equivalent of the popular US Green Card. The 'Blue Card' act streamlined visa application and right of residence procedures for skilled professionals from abroad. Additionally, relatives of the applicant could receive a work permit in parallel.
Japan	2010	Policies for Foreign Residents of Japanese Descent	Increase Rights	The policy guidelines promoted the acceptance of Japanese descendants who lack language proficiency. As part of the guidelines, the government will provide daily life support including connecting such immigrants with employment offers.
Japan	2012	Point System for Highly Skilled Foreign Professionals	Increase Volume	A point-based system was established to attract highly-skilled foreign professionals. Three types of professionals are given preferential immigration treatment: advanced academic researcher, advanced specialist/technician and advanced business managers. In each category, points were given to academic achievement, work experience, annual income and other factors. If total points reach 70, the professional will be granted a status of residence.

Table B.1: Descriptions of Study Reforms (Continued)

Country	Year	Title	Impacts	Brief Description
Mexico	2010	The Migratory Procedures and Criteria Manual of 2010	Increase Volume	Introduction of standardized procedures for migration officers including a new manual for immigration decisions. The manual simplified immigration forms and online application procedures. A new centralized information system (SETRAM) was also implemented to remove discretionary decision-making by case officers.
Mexico	2011	Migratory Act of May 25th	Increase Rights, Increase Volume	The act represented a substantial liberalization of migration policy, with a particular emphasis on easing migration for foreign workers. The law guaranteed foreigners the right to education, health services and judicial rights, and introduced four new categories of immigration permits: Visitor, Student, Temporary Resident, and Permanent Resident. The law established the Center for Evaluation and Control of Trust, which oversees immigration authorities and standardized their practices.
Portugal	2001	Law-Decree no. 4/2001	Increase Volume	A new temporary work visa category "stay permit" was created for foreigners who have a work contract. The stay permit was valid for one year with the possibility of extending to a maximum of five years. Foreigners were allowed to bring their family members to the Philippines and at the end of the five-year period, foreigners could apply for a resident permit.
South Korea	2009	Contact Korea	Increase Volume	Contact Korea is an online platform for global skilled labor to apply for jobs in both private and public sectors in South Korea. The platform standardizes the application process and provides market a connecting employers, applicants, and immigration processes. It serves as a one-stop shop by providing services such as arranging online interviews, verifying academic and professional background and dealing with visa and immigration issues.
South Korea	2010	HuNet Korea Immigration Network	Increase Volume, Increase Rights	A new online visa application system (HuNet Korea) would be implemented to standardize visa and job applications for foreign professionals and students as well as their spouses. Additionally, a point system was implemented for professionals who wish to obtain resident or permanent resident status in Korea. The program included increasing the number of sites for naturalization interview tests to facilitate immigrant naturalization.

Table B.1: Descriptions of Study Reforms (Continued)

Country	Year	Title	Impacts	Brief Description
Spain	2003	Organic Law 14/2003 - Amendment to Organic Law 8/2000	Increase Rights, Increase Volume	This amendment increased rights for families of legal foreigners. For example, a spouse could obtain a residence permit when given a work permit and provisions were added for children to apply for residence permits upon reaching adulthood. Additionally mandated yearly government review of foreign worker permit quotas.
Spain	2009	Organic Law 2/2009 - Amendment to Organic Law 4/2000	Increase Rights	This amendment added a series of articles increasing the rights of immigrants and focusing on their integration. Examples include extending voting rights in municipal elections to foreign residents, granting foreigners healthcare under the same condition as citizens, and providing a pathway for highly qualified migrants to obtain a residence permit and EU blue card.
United Kingdom	2006	Immigration, Asylum and Nationality Act	Increase Rights	Act established a five-tier points system for awarding entry visas that included carving out specialized visas for both skilled workers and temporary workers that positively select based on accumulated skills. The act further included restrictions on appeals of immigration decisions as well as additional penalties for illegal employment of foreigners.

B.1.2 Construction of a Database of Migration Reforms

Collecting Reforms

In constructing a sample of reforms, our starting point was the work of Branstetter et al. (2006), who indexed global intellectual property reforms previously. The countries indexed in the final data are: Brazil, Canada, Chile, China, Germany, India, Italy, Japan, Mexico, the Philippines, Portugal, South Korea, Spain, Taiwan, and the United Kingdom. Countries were selected based on the presence of (i) historical enactment of intellectual property legislation supportive of patenting, (ii) multinational activity, and (iii) significant migration flows. Ten of these countries coincide with the sample analyzed in Branstetter et al. (2006), who study the impact of systematic reforms designed to strengthen and standardize intellectual property on MNEs' resulting foreign direct investments between 1982 to 1999. Relative to that study, we expanded the sample to 5 additional countries with the aim of including countries that are the source and destination of significant migration flows. For instance, Canada and the United Kingdom are in the top four most frequent destinations of OECD migration in 2010, while India, the Philippines, and the United Kingdom, experienced the most net emigration in 2010 (Kerr et al., 2016). Additionally, several of the countries in the list are representative of high levels of net inventor immigration.

After identifying a list of countries, we turned to collecting reforms. During the period of 2017 through summer 2019, a team of RAs and the authors identified migration policy reform events impacting high-skilled human capital migration of two types into a focal country: (1) return migrants, and (2) foreign immigrants. Alongside identification, the team collected corresponding primary and secondary sources related to reforms. Collection occurred in two waves - the first in 2017 and the second in Winter 2018 to Summer 2019 - and focused on ensuring complete collection of reforms enacted in the period of 2000 to 2014. Where additional reforms were identified outside this period, they were included in the dataset. As a result, the database of reforms is primarily useful for analyses on the post-2000 era and is less reliable for reforms and initiatives prior to this point.

In the second wave, collection of reforms preceded following a standardized heuristic with emphasis on ensuring completeness in the dataset. First, a search was conducted to collect any primary or secondary news sources related to the countries under review from websites that focused on information related to migration policies and programs of countries, including websites focused on assisting immigration and websites focused on the navigating migratory legislative policies of countries. Example websites include: LegislateOnline, (`http://www.legislationline.org/`); The Library of Congress, (`https://www.loc.gov/law/help/migration-citizenship/`); and that of the think tank Migration Policy (`http://www.migrationpolicy.org`). Website-based searches would also turn to legal codes of countries published online by their central governments, searching explicitly for links and connections to the codified migration laws of a country (e.g., legal codes of all European Union countries are indexed on EU websites). After website searches, academic repositories were searched for articles with comprehensive explanation of migration policy reforms and initiatives. Finally, these searches were followed by a series of keyword based searches implemented in the Wikipedia online encyclopedia (`https://www.wikipedia.org/`) and Google's web search engine focused on identifying articles, information, and primary sources related to migration policy reforms, migration policy initiatives, and high skilled human capital immigration into and out of a country. Iteration between approaches occurred as necessary (for example, if Wikipedia revealed several individual laws to search for or programs to search for, the researcher would spend time looking for primary sources for those laws or programs in legal code and government websites). Table B.2 provides a list of example searches

Table B.2: Example Keyword Terms Leveraged in Search

Wikipedia	Google: HS HC	Google: Catch-All
1. Migration in <Country>	1. Entrepreneurship Immigration <Country>	1. Move to <Country>
2. History of Migration in <Country>	2. Start a Business as an Immigrant <Country>	2. Immigrate to <Country>
3. Migration Policy <Country>	3. STEM Incentives <Country>	3. Immigration to <Country> <Nationality> Heritage
4. <Nationality> Citizenship	4. High Skill Migration <Country>	4. Migration Policy <Country>
5. Citizenship in <Country>	5. Refugee Immigration <Country>	5. History of Migration <Country>

utilized in the search process.

Categorizing Reforms

To characterize the anticipated impacts of reforms, the authors qualitatively assessed each reform and the associated primary and secondary sources. Based on this analysis, reforms were coded according to whether the anticipated effects were positive (easing movement) or negative (restricting movement) based on how the reforms impacted legal migration frameworks of countries. Specifically, reforms were classified as positive or negative according to anticipated impact along three dimensions: (i) the rights of a migrant (either foreigners or returnees), (ii) the expected volume of migrants post reform, and/or (iii) the duration of stay or required time to achieve residency status criteria associated with admission to a country. Reforms identified as generating increases (alt. decreases) along any of these dimensions were then codified as having a positive (alt. negative) effect. While rare, some reform packages simultaneously enacted provisions exhibiting both positive and negative effects. For such reform events, we treat the event as an instance of both a positive reform and a negative reform. For example, in 2013, China enacted administrative regulations that increased the number of visas awarded, with the impact of increasing work rights for certain migrants (e.g., foreign students with an X-class visa were then allowed to work off-campus) while also decreasing rights for others (e.g., instilling greater penalties for illegal employment). As a result, this reform is coded as a positive reform event for China in 2013 and also a negative reform event for china in 2013.

In addition, we coded the main mechanisms through which the reforms work, broken into four categories: business training and recruitment, education, entrepreneurship and capital investment, and science, technology, and innovation. The selection of mechanisms was determined through both consideration of migration mechanisms suggested in the academic literature as well as through inductive, emergent classification. The mechanisms were individually defined as:

- **Business Training and Recruitment** – These reforms and initiatives involve impeding or easing access to transient workers of firms. This includes changes to rights, privileges, and duration of short-term work-related visits, of long-term movements related to worker recruitment and migration, and of MNEs' ability to preferentially select migrants. These reforms were further coded into those impacting 'permanent', long-term business-related travel, with impacts on immigration of periods of a year or longer, or those impacting 'temporary', short-term business-related travel, with impacts on immigration periods of less than a year. Examples include new restrictions in Mexico in 2012 prohibiting immigrants from switching from visitor to work visas; and the implementation of an online platform for travel visa application and approval in South Korea in 2009.

- **Education** – These reforms and initiatives involve the award of visas and special rights to individuals participating in all levels of university education. Examples include China's enactment in 2008 of the 'Thousand Talents Plan', which provided monetary awards to scholars of Chinese heritage who returned to Chinese universities to engage in research; a 2011 'young talents' scholarship enacted in Brazil to attract undergraduate students of Brazilian heritage to study in Brazilian colleges; and the enactment in 2012 of a point-based system in Japan for awarding residency that was weighted heavily towards academic research.

- **Entrepreneurship and Capital Requirements** – These reforms involve promoting entrepreneurial business and capital investment via migration policy. The reforms largely take two types. The first is entrepreneurial-oriented reforms focused on providing funding and general support (e.g., information, training) to migrants or returnees seeking to create a business in the focal country. A well-known example of such initiatives is the 'Start-Up Chile', an entrepreneurial accelerator founded in 2010 and funded by Chilean government ministries, that was aimed at attracting foreigner entrepreneurs. The second common type of reform in this category are those that provide visas or permanent residency in exchange for capital investment by individuals. An example is the 2012 Portuguese 'Golden Visa Scheme', which awarded permanent residency and expedited paths to citizenship to individuals who invested at least one million Euro or created ten or more jobs.

- **Science, Technology, and Innovation** – These reforms and initiatives focused on the attraction and retention of professionals engaged in scientific, technological, or innovation-related work, either foreigners or citizens abroad. Initiatives in our sample include Germany's 2001 and 2004 adjustments to the Green Card initiative, which targeted recruitment of foreign experts in the ICT industry; and the initial funding of the International Science Business Belt program in South Korea in 2011, which set aside government funding for a large basic-science initiative that sought to attract and provide incentives for top academic science talent to migrate to South Korea and to also foster international research collaborations. These policies also include reforms towards "points-based" migration systems that select for highly-educated professionals or the adjustments of access rights of such professionals (e.g., Spain's institution of Organic Law 4/2000 that, in part, removed work permit requirements for certain scientists or technicians).

Describing Reforms

Table B.3: Reform Type Counts by Country

		Returnee		Foreigner		Mechanisms			
Country	Total	Positive	Negative	Positive	Negative	Bus. T&R	Edu.	Ent. & Cap.	Sci., Tech., & Innov.
Brazil	3	1	0	2	0	1	1	1	2
Canada	10	3	2	3	3	2	0	0	1
Chile	6	5	0	1	0	1	3	1	3
China	6	3	0	2	3	1	4	0	4
Germany	7	1	1	4	1	4	2	1	4
India	4	2	1	1	0	0	1	0	1
Italy	8	2	1	1	4	1	0	0	0
Japan	10	3	0	6	2	3	2	2	2
Mexico	8	1	0	5	2	4	1	1	0
Philippines	7	2	0	2	3	4	0	0	0
Portugal	4	0	0	3	2	3	0	1	1
South Korea	9	2	0	7	0	5	3	2	4
Spain	4	0	0	3	1	2	1	0	1
Taiwan	3	1	0	2	0	1	1	0	0
United Kingdom	12	1	2	3	6	2	2	1	1
Total (2000 - 2014)	101	27	7	45	27	34	21	10	24

Notes: The table presents counts of reform types indexed by country for the reforms covered in the main sample constrained to the years 2000 to 2014. The classifications for reform mechanisms are: Bus. T&R = Business Training and Recruitment; Edu. = Education Sector Related reforms; Ent. & Cap. = Entrepreneurship and Capital Requirement reforms; Sci., Tech., & Innov. = Science, Technology, and Innovation reforms.

Table B.3 presents counts summarizing reform distribution across countries by immigrant type affected (returning citizen vs. foreigner) for only those reforms during the years 2000 - 2014. Most countries in our sample have at least 3 reforms between the 15 years, while some countries (such as Canada, Japan and the United Kingdom) have more than 10. A large majority of reforms - 71% - target foreigners while only 33% explicitly targeted returnee migrants. Reforms during the period leaned towards positive interventions, anticipated to increase migration, with 72 identified instances of anticipated positive effects and only 34 identified anticipated negative effects. During the period, reforms predominantly worked through the mechanism of Business Training and Recruitment (34 reforms total and only one country, India, was identified to not have enacted such a reform). However, education-related and science, technology, and innovation-related reforms likewise represent large portions of the total set of reforms observed. Reforms enactments were clustered within countries, such that if a country enacted many reforms of one type, they were more prone to enact other reforms as well.

Table B.4 outlines the pathway of reform events over time. For each reform classification, it provides information on the number of reforms enacted by year as well as the cumulative number of countries enacting a reform. Readily evident is that most reform classifications are never enacted among all countries during the years of the sample (only reforms targeting foreigners with anticipated positive effects are enacted at least once in each country), with some reforms enacted only among a minority of countries in the sample (e.g., negative entrepreneurship and capital requirement related reforms, or negative education related reforms). Certain reform types cluster within countries over time and only diffuse throughout the sample slowly, while others diffuse quickly and early on. In the period of 2000 to 2006, for example, positive returnee reforms are multiply enacted at least three times and are only observed in seven countries by the end of 2006. By contrast, positive reforms targeting foreigners are enacted throughout nine countries in the three years of 2000 to 2002, without repetition. By 2006, 16 reforms of this type are enacted across 11 countries.

B.2 Global Collaborative Patenting Activity Over Time

For assistance understanding the change in patenting activity over time and globally within the patent data, Figure B.1 displays the count of assignees measured to produce GCPs over time and the number of countries measured to produce GCPs over time (black solid and black dashed lines respectively) as well as the number of patents produced over time and the number of GCPs produced over time (grey solid and dashed lines respectively) in the geocoded data from all USPTO patents during the years 1965 to 2016 indexed in the UCB Fung Institute data sample.

Table B.4: Reforms Type Counts Over Time

Reform	Metric	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	Total
Reforms By Immigrant Population Targeted																	
Positive Returnee	Num. Reforms	3	0	2	3	0	1	1	2	2	5	2	4	0	0	2	27
	Cumulative Countries	3	3	5	7	7	7	7	9	10	11	11	13	13	13	13	13
Negative Returnee	Num. Reforms	1	0	2	0	0	0	1	0	0	1	1	0	0	0	1	7
	Cumulative Countries	1	1	3	3	3	3	3	3	3	4	4	4	4	4	5	5
Positive Foreigner	Num. Reforms	4	3	2	1	2	2	2	0	4	4	3	2	4	2	7	42
	Cumulative Countries	4	7	9	9	10	11	11	11	12	13	13	13	13	13	15	15
Negative Foreigner	Num. Reforms	1	1	3	1	4	1	2	1	0	3	1	1	3	1	1	24
	Cumulative Countries	1	2	4	5	8	9	9	9	9	10	10	10	10	10	10	10
Reforms By Mechanism																	
Bus. Training & Recruiting (Pos.)	Num. Reforms	1	1	1	1	2	2	1	0	0	2	2	1	3	1	4	22
	Cumulative Countries	1	2	3	4	5	6	7	7	7	7	8	8	9	10	12	12
Bus. Training & Recruiting (Neg.)	Num. Reforms	0	1	1	1	2	0	1	0	0	1	0	0	3	0	0	10
	Cumulative Countries	0	1	2	3	5	5	6	6	6	7	7	7	8	8	8	8
Education (Pos.)	Num. Reforms	0	0	0	0	1	1	1	0	1	2	0	2	3	0	1	12
	Cumulative Countries	0	0	0	0	1	2	3	3	4	6	6	7	7	7	8	8
Education (Neg.)	Num. Reforms	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	2
	Cumulative Countries	0	0	0	0	1	1	2	2	2	2	2	2	2	2	2	2
Entrepreneurship & Capital Reqs. (Pos.)	Num. Reforms	0	0	1	0	0	1	1	0	0	1	0	0	2	0	1	7
	Cumulative Countries	0	0	1	1	1	2	3	3	3	3	3	3	5	5	5	5
Entrepreneurship & Capital Reqs. (Neg.)	Num. Reforms	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1
	Cumulative Countries	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1
Sci., Tech., Innov. (Pos.)	Num. Reforms	2	0	1	0	1	1	1	0	0	1	0	1	4	0	2	14
	Cumulative Countries	2	2	3	3	4	4	5	5	5	5	5	5	7	7	8	8
Sci., Tech., Innov. (Neg.)	Num. Reforms	0	1	0	0	2	0	0	0	0	0	0	0	1	0	0	4
	Cumulative Countries	0	1	1	1	3	3	3	3	3	3	3	3	4	4	4	4

Notes: The table presents counts of reform types over time for the reforms constrained to the years 2000 to 2014, aggregated across countries. The top row of each reform category type, Num. Reforms, illustrates the number of reforms of that type enacted in the focal year across the countries examined. The second row of each category type, Cumulative Countries, represents a count of the unique number of cumulative countries to enact a reform of the corresponding type by the focal year. The final column provides total counts for the full scope of the sample (either total number of reforms of a type enacted across 2000 - 2014, or total number of unique countries to ever enact a reform of the given type).

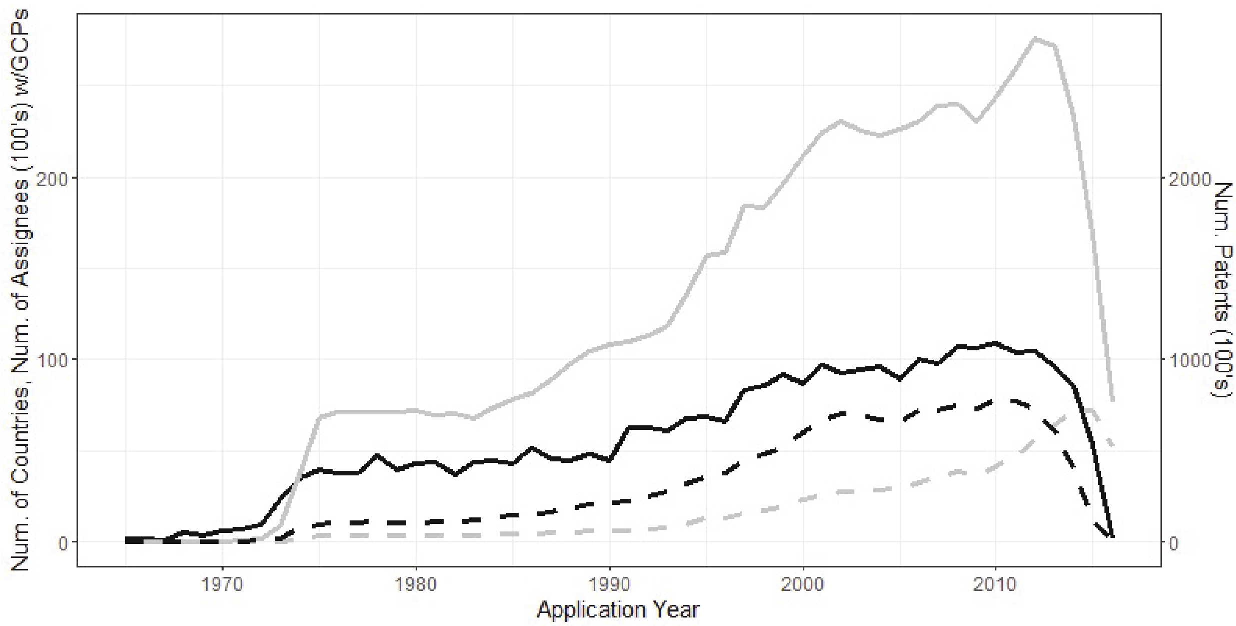


Figure B.1: Global Collaborative Patent Applied for During Years 1965 - 2016
Notes: The black solid line displays the count of assignee firms with global collaborative patents, and the black dashed line displays the count of unique countries with GCPs among all countries. The grey solid line displays the count of patents produced, and the grey dashed line displays the count of GCPs produced over time. Notable rightward censuring begins in the data after 2014.

B.3 Estimation of Treatment Effects Give Frequently Repeated and Clustered Events

B.3.1 A Generalized Estimator

In a classical difference-in-differences or event-based approach, the key term of interest is an indicator variable or series of relative event-time indicators that take the value one in the periods of and subsequent to treatment. The coefficient on this key term estimates the mean difference in the response in the period(s) surrounding treatment with emphasis on those subsequent to treatment.[1] This model is inflexible in the case of repeated treatment, and standard practice is to discard observations where repeated treatment occurs. This is not feasible in all situations, however, including those where treatment events are clustered at the

[1] Borusyak and Jaravel (2017) presents canonical equations that outline the generalized event-based estimator and which relate difference-in-differences specifications to event study specifications by demonstrating that the estimator is a specific case of a more general event-study specification with dynamic treatment effects. Goodman-Bacon (2018) examines the case of difference-in-differences estimation conditional on variation in treatment timing, shows that the treatment effect estimated is a weighted average of the treatment effect of the component difference-in-differences estimates, and proposes a test for the validity of such estimators.

level of the group among observations with few group categories or where treatment events are clustered in time, as in our data.

To accommodate, we relax the requirement that the time periods examined in the difference-in-differences estimator include only the singular enactment of an event, and we treat the difference-in-differences estimator key term as a non-negative count of events enacted that can vary over time. Generalizing from the regressions in our analyses, we allow variations on models of the general form:

$$Y_{it} = f(\gamma_i + \gamma_t + \beta \; r_{it}; \; \epsilon_{it})$$

where Y_{it} represents the response variable in time t for observation group i, γ indexes time and group fixed effects, and r_{it} is the count of treatment events implemented to date for group i in time t, and ϵ_{it} is the standard error term.[2] When only a singular event is ever enacted for any given observation, this model is equivalent to classical difference-in-differences or event-based approaches that include fixed effects that subsume the independent effects of time and treatment.

In this model, the key coefficient of interest is β, and it is interpreted as the average per-period increase in the response conditional on an additional event. For simplicity, the measurement r_{it} assigns equal weight to each consecutive reform of the same type, and as a result imposes the restriction that the average treatment effects of a given reform event type must be equivalent across reform events.

A generalized version of this measure might estimate treatment effects independently, including linearly-additive indicators for each level of consecutive treatment such that $r_{it} = \sum_j^J \sum_{t=0}^{T=t} \mathbb{1}(event_{it,j})$ where j indexes the various levels of treatment and where coefficients are estimated for each level of j. To economize on statistical power and maintain simplicity, we impose the restriction of equivalence in effect across treatment levels in our analyses.

Causal inference given this estimator requires additional assumptions. Literature on causal inference in the presence of repeat events (e.g., Blackwell 2013) suggests two. First, it is necessary to assume that treatment events are linearly additive in their effects and exhibit independence otherwise, with no interaction across treatment levels. Second, it also must be assumed that treatment is orthogonal to the consequences of the treated unit's prior treatment history - i.e., future treatment and impacts on the response are not

[2] In other words, $r_{it} = \sum_{t=0}^{T=t} \mathbb{1}(event_{it})$.

significantly determined by the prior sequence of past treatment.

B.3.2 Simulation of Estimator Measurement Error

To evaluate whether this estimator accurately measures the corresponding causal treatment effect, we conducted computational simulations in which data based on parameters in our setting were simulated and the model fit repeatedly across several simulations. Specifically, for each simulation s, data were generated from the following process involving 'Reform Events' across 8 years (y) affecting 15 'Countries' (c) and 10 'Firms' (f) present within those countries (where other parameters were chosen to approximate sample means in the actual data observed where possible[3]):

1. **Simulate Country Treatment Pathways:** A treatment event pathway was assigned for each simulated country with random variation in the frequency of treatment events within a given country that was defined by random variation in the probability of treatment event occurrence across countries. This occurred in two steps:

   (a) **Assign Random Country-Level Probability of Per-Year Treatment From Uniform Distribution:** $p_{cs} \sim \mathcal{U}(0, 0.4)$

   (b) **Determine Treatment Pathway From Binomial Distribution:** $T_{cys} \sim \mathcal{B}(p_{cs})$

2. **Simulate One-Way Fixed Effects:**

   (a) **Simulate Assignee Fixed Effects:** $\gamma_{fs} \sim \mathcal{N}(\mu = 10, \sigma = 3)$

   (b) **Simulate Year Fixed Effects:** $\gamma_{ys} \sim \mathcal{N}(\mu = 0, \sigma = 3)$

   (c) **Simulate Country Fixed Effects:** $\gamma_{cs} \sim \mathcal{N}(\mu = 0, \sigma = 3)$

3. **Simulate Two-Way Fixed Effects:**

   (a) **Simulate Assignee-Year Fixed Effects:** $\gamma_{fys} \sim \mathcal{N}(\mu = 0, \sigma = 3)$

   (b) **Simulate Country-Year Fixed Effects:** $\gamma_{cys} \sim \mathcal{N}(\mu = 0, \sigma = 3)$

   (c) **Simulate Subsidiary (Assignee-Country) Fixed Effects:** $\gamma_{fcs} \sim \mathcal{N}(\mu = 0, \sigma = 3)$

[3] While fixed effects are estimates from a consistent normal distribution, the results prove robust to estimating fixed effects based on by-variable mean and standard deviation point estimates from a regression on the data that only includes fixed-effect terms.

4. **Simulate Random Noise:** $\epsilon_{fcys} \sim \mathcal{N}(\mu = 0, \sigma = 1)$

5. **Simulate Treatment Effect w/Random Variance Across the Year-Firm-Country Level:** $D_{fcys} \sim \mathcal{N}(\mu = 3, \sigma = 1)$

6. **Compute Linearly-Additive Response Based on Differing Treatment Modes:**

   (a) **Treatment Affects Rate:** $y_{fcps} = \gamma_{fs}+\gamma_{cs}+\gamma_{ys}+\gamma_{fcs}+\gamma_{fys}+\gamma_{cys}+\sum_{t=0}^{T=t}(T_{cys})\times D_{fcys}+\epsilon_{fcys}$

   (b) **Treatment Affects Level:** $y_{fcps} = \gamma_{fs} + \gamma_{cs} + \gamma_{ys} + \gamma_{fcs} + \gamma_{fys} + \gamma_{cys} + T_{cys} \times D_{fcys} + \epsilon_{fcys}$

For each of 5,000 simulations, we then fit the following regressions:

$$y_{fcps} = \gamma_{fs} + \gamma_{cs} + \gamma_{ys} + \beta r_{cys} + \epsilon_{fcys} \qquad \text{Cumulative Estimator}$$

$$y_{fcps} = \gamma_{fs} + \gamma_{cs} + \gamma_{ys} + \beta T_{cys} + \epsilon_{fcys} \qquad \text{Panel Estimator}$$

where the first equation corresponds to estimating the treatment effect on the cumulative count of events and the second equation corresponds to a panel estimator where the variable of interest takes the value one in periods where the event occurs and zero otherwise. For the resulting key coefficient of interest (β), we calculated the variance of the resulting estimates and their mean squared error defined as the mean of the square of the differences between the estimate and the actual treatment effect (MSE $= \frac{1}{5,000}\sum(3-\beta)^2$).

Table B.5: Efficiency of Estimator

Model	Estimator	$\mu(\beta)$	Var.(β)	MSE	$\frac{MSE}{TreatEffect}$	$\frac{Var.(\beta)}{TreatEffect}$
Rate	Cumulative	3.006	0.349	0.349	0.116	0.116
Rate	Panel	1.475	0.794	3.120	1.040	0.265
Level	Cumulative	0.783	0.406	5.319	1.773	0.135
Level	Panel	2.984	0.688	0.688	0.229	0.229

Notes: This table provides the results from simulations designed to evaluate the efficiency of the 'cumulative events' estimator.

Table B.5 displays the resulting estimates. Readily apparent is that the panel estimator is best suited for contexts where treatment produces a single-period shock to the response and in such cases it estimates closely the real average treatment effect. However, in the case of repeated events, the cumulative estimator most closely reflects the real average treatment effect. Additionally, when applied to the outcome derived from a model in which treatment influences the rate of the response, the cumulative estimator yields the lowest variance in the estimates as well as the lowest mean squared error across all specifications. Overall, we interpret this as strong evidence for the statistical validity of the cumulative estimator.

B.4 Additional Results and Robustness Check

This section includes various robustness checks of the results presented in Chapter 2. These are: evaluating the main effects via Poisson regressions; evaluating the main effects while defining exposure as the mean (as opposed to max) count of active sister affiliates; demonstrating that by-period event study estimates are robust to excluding cutoff indicators in estimation; and demonstrating that heterogeneity by MNE size is robust to allowing MNE size to vary over time,

B.4.1 Poisson Specification

Table B.6: Poisson Pseudo-Likelihood Fixed Effects Regression

	All MNE Patents			Migrant Inv. Patents		
	(1)	(2)	(3)	(4)	(5)	(6)
	pat_{fct}	gcp_{fct}	dom_{fct}	$mig1yr_{fct,pat}$	$mig1yr_{fct,gcp}$	$mig1yr_{fct,dom}$
Cumulative Reforms	0.019*	0.0087*	0.044**	0.012+	0.0044	0.037***
$(r_{ct}) \times exp_{fct}$	(0.0076)	(0.0042)	(0.014)	(0.0071)	(0.0047)	(0.010)
exp_{fct}	-3.29***	-1.81***	-8.48***	-2.62***	-1.39***	-7.80***
	(0.089)	(0.060)	(0.24)	(0.094)	(0.090)	(0.37)
Constant	39.6***	26.4***	87.1***	35.2***	22.0***	88.4***
	(0.98)	(0.81)	(2.31)	(1.24)	(1.38)	(4.07)
MNE X Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country X Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N. Obs	173,132	142,739	69,418	59,425	43,159	23,617
Chi Sqrd.	1590.4	916.5	1323.6	837.9	243.7	453.9
Psuedu R2	0.72	0.60	0.76	0.53	0.48	0.60
log like.	-3679465.6	-809736.9	-2541379.9	-181582.4	-72936.5	-103789.4

Notes: The table shows the results of high-dimensional fixed effects Poisson quasi-maximum-likelihood regressions of patent counts on exposure and cumulative reforms among the sample of retained observations (non-singletons). The first three columns show estimated coefficients for effects on total patents produced by MNE subsidiaries while the final three columns show the estimates for only migrant patents produced by MNE subsidiaries within one year of an inferred migrant move. Robust standard errors for estimates are in parenthesis. Significance Levels: $+\ p < 0.10$, $*\ p < 0.05$, $**\ p < 0.01$, $***\ p < 0.001$.

Table B.6 refits the estimates calculated in Table 2.5 but leveraging untransformed patent count indices as the dependent variable and estimating coefficients via high-dimensional fixed effects Poisson regression methods, which are well-suited to spare count dependent variables. The results demonstrate positive and significant effects of reforms on MNE subsidiary forward production of patents, GCPs, and domestic patents, as well as forward production of patents produced by migrant inventors and domestic patents produced by migrant inventors. While positive, the effect estimated on GCP production by migrant inventors is insignificantly identified. These results leverage significantly less of the sample, however, and therefore are primarily used to support the findings presented in the chapter.

B.4.2 Mean Exposure Specification

Table B.7 refits the estimates calculated in Table 2.5 but computes the exposure measure, exp_{fct}, as the mean count of actively patenting sister-affiliates observed over the five years prior to time t. The results estimate similar point estimates to those in Table 2.5, but lack significance with respect to estimates of the impact of the migration policy reforms on domestic patents, by all inventors or by migrants. Overall, these results provide evidence for the robustness of the effects identified on overall patent production and GCP production.

Table B.7: Business Reforms and Patenting - Mean Exposure Measure

	All MNE Patents			Migrant Inv. Patents		
Arcsinh Transformed:	(1) pat_{fct}	(2) gcp_{fct}	(3) dom_{fct}	(4) $mig1yr_{fct,pat}$	(5) $mig1yr_{fct,gcp}$	(6) $mig1yr_{fct,dom}$
Cumulative Reforms	0.0061*	0.0065*	0.0016	0.0039*	0.0037*	0.0011
$(r_{ct}) \times exp_{fct}$	(0.0027)	(0.0027)	(0.0021)	(0.0019)	(0.0017)	(0.0011)
exp_{fct}	-2.13***	-1.08***	-1.49***	-0.44***	-0.17***	-0.30***
	(0.029)	(0.020)	(0.035)	(0.015)	(0.0078)	(0.015)
Constant	4.26***	2.23***	2.86***	0.86***	0.35***	0.57***
	(0.054)	(0.038)	(0.065)	(0.028)	(0.014)	(0.027)
MNE X Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country X Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N. Obs	361,452	361,452	361,452	361,452	361,452	361,452
Adj. R	0.42	0.35	0.23	0.03	-0.01	-0.07
Adj. R Within	0.37	0.20	0.27	0.10	0.03	0.08

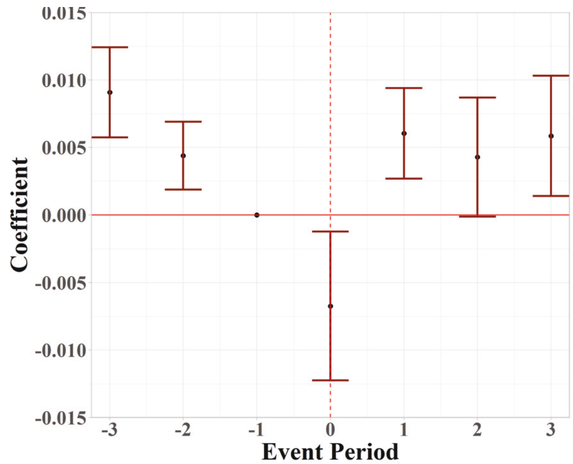
Notes: The table shows the results of high-dimensional fixed effects regressions of arcsinh transformed patent counts on exposure - defined via the mean of observed sister affiliate activity - and cumulative reforms among the sample of retained observations (non-singletons). The first three columns show estimated coefficients for effects on total patents produced by MNE subsidiaries while the final three columns show the estimates for only migrant patents produced by MNE subsidiaries within one year of an inferred migrant move. Cluster-robust standard errors at the subsidiary level (Country-Firm) for estimates are in parenthesis. Significance Levels: $+\ p < 0.10$, $*\ p < 0.05$, $**\ p < 0.01$, $***\ p < 0.001$.

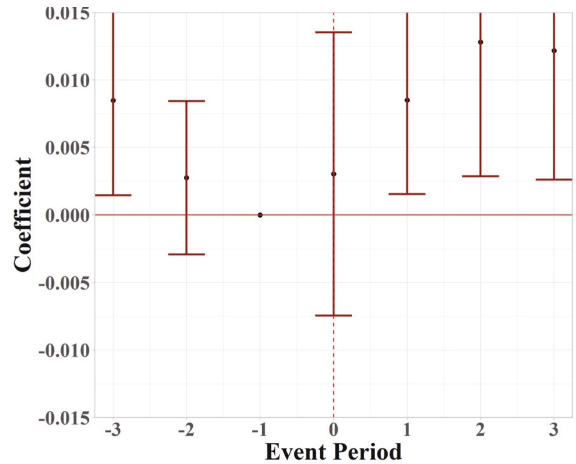
B.4.3 Event Study, Cutoffs Omitted

To demonstrate robustness of dynamic treatment effects estimates, Figures B.2 and B.3 replicate the results of Figure 2.2 and Figure 2.3, respectively, while omitting cutoff indicators from estimation (reflected by the absence of cutoff point estimates). The figures identify similar event-time point estimates to those presented in the main results of the study.

B.4.4 Time Variation in MNE Size

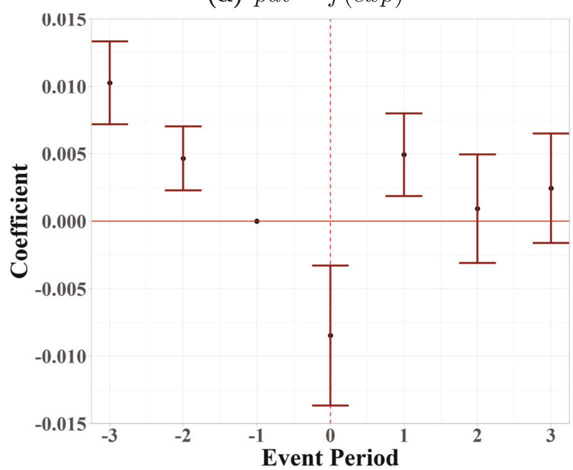
Figure B.4 replicates the results of Figure 2.4, but allows MNE size to vary with time. Specifically, the measure for MNE size in time t is calculated as the average of total patent production by the MNE in the 10 years prior to the time t, and MNEs are split into groups above mean production in year t or at or below mean production in year t. The results demonstrate that positive returns of migration policy reforms to MNEs in both groups, but that the returns are significantly larger among MNEs of above mean size, in line with the findings in the chapter.

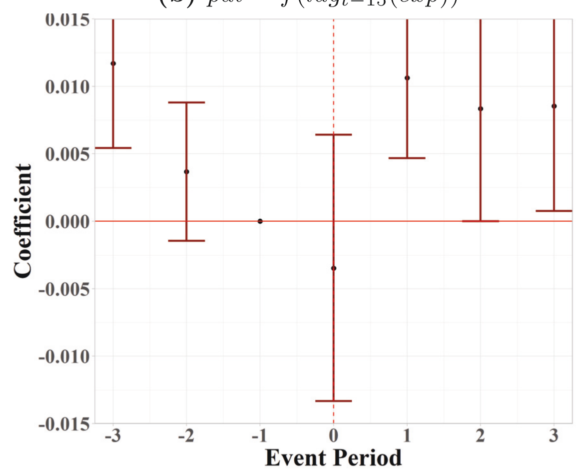




(a) $pat = f(exp)$

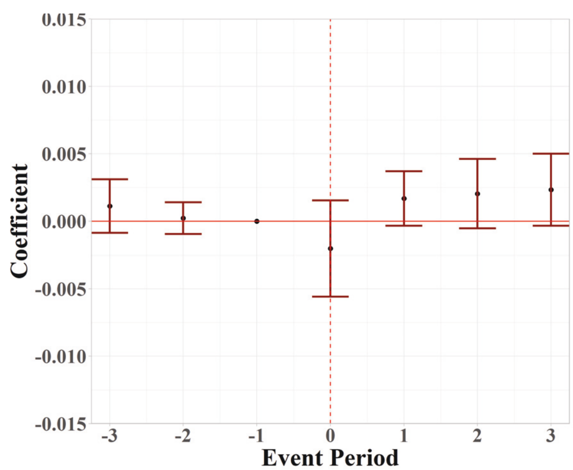
(b) $pat = f(lag_{t-15}(exp))$

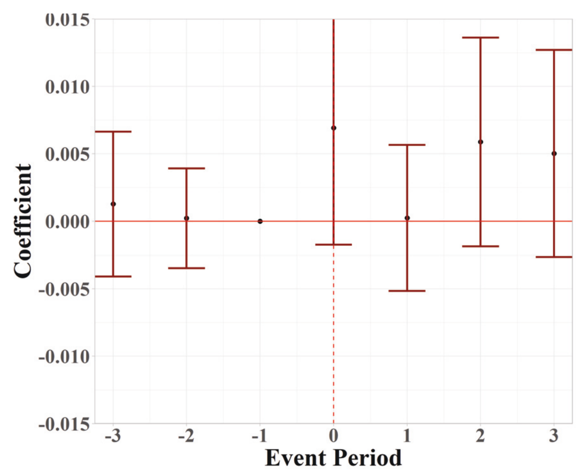




(c) $gcp = f(exp)$

(d) $gcp = f(lag_{t-15}(exp))$



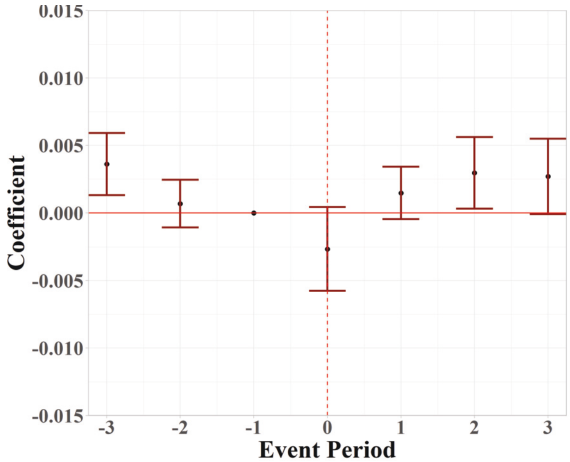


(e) $dom = f(exp)$

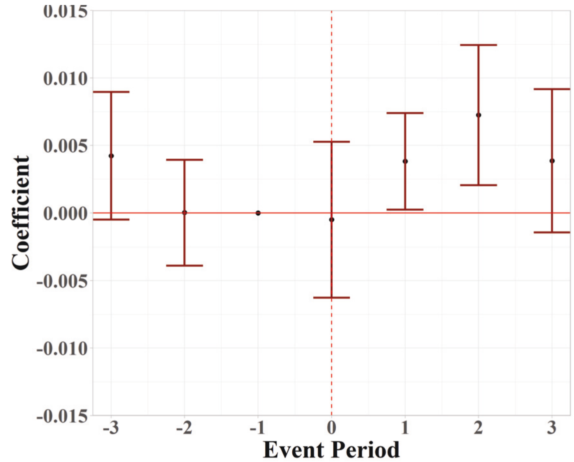
(f) $dom = f(lag_{t-15}(exp))$

Figure B.2: Dynamic Treatment Effects of Reforms on All MNE Patents, No Cutoffs

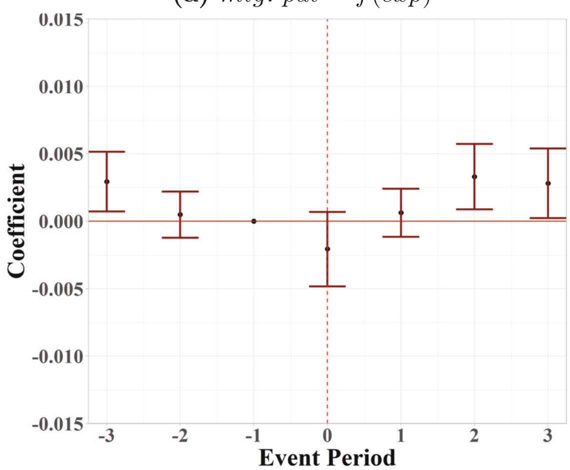
Notes: The figure displays the coefficients and confidence intervals of $r_{ct} \times exp_{fct}$ in regressions of all MNE patents. The left column displays simple OLS regression with contemporaneous exposure, while the right column displays reduced form results with historic exposure. The first row corresponds to total patents, the second row GCPs, and the third row DOMs. Whiskers reflect 95% confidence intervals for point estimates. Cutoff coefficients are omitted from estimation.



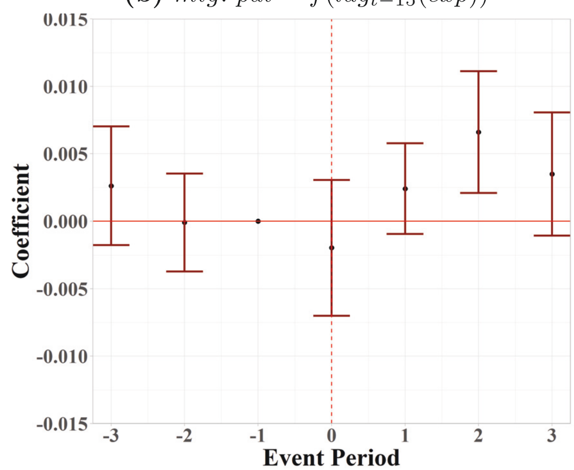
(a) $mig.\ pat = f(exp)$



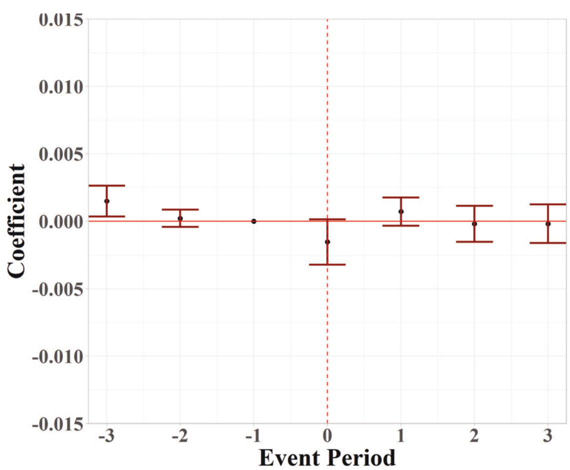
(b) $mig.\ pat = f(lag_{t-15}(exp))$



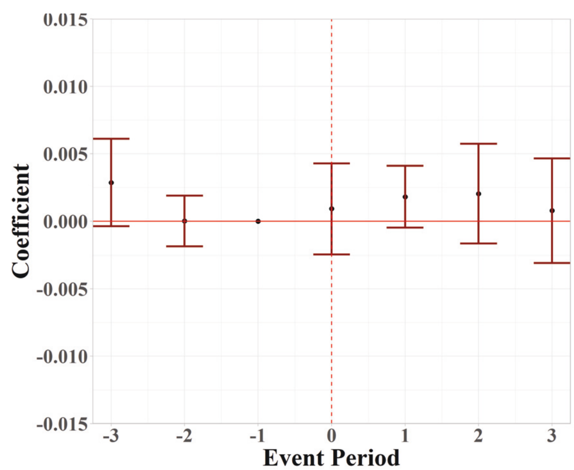
(c) $mig.\ gcp = f(exp)$



(d) $mig.\ gcp = f(lag_{t-15}(exp))$



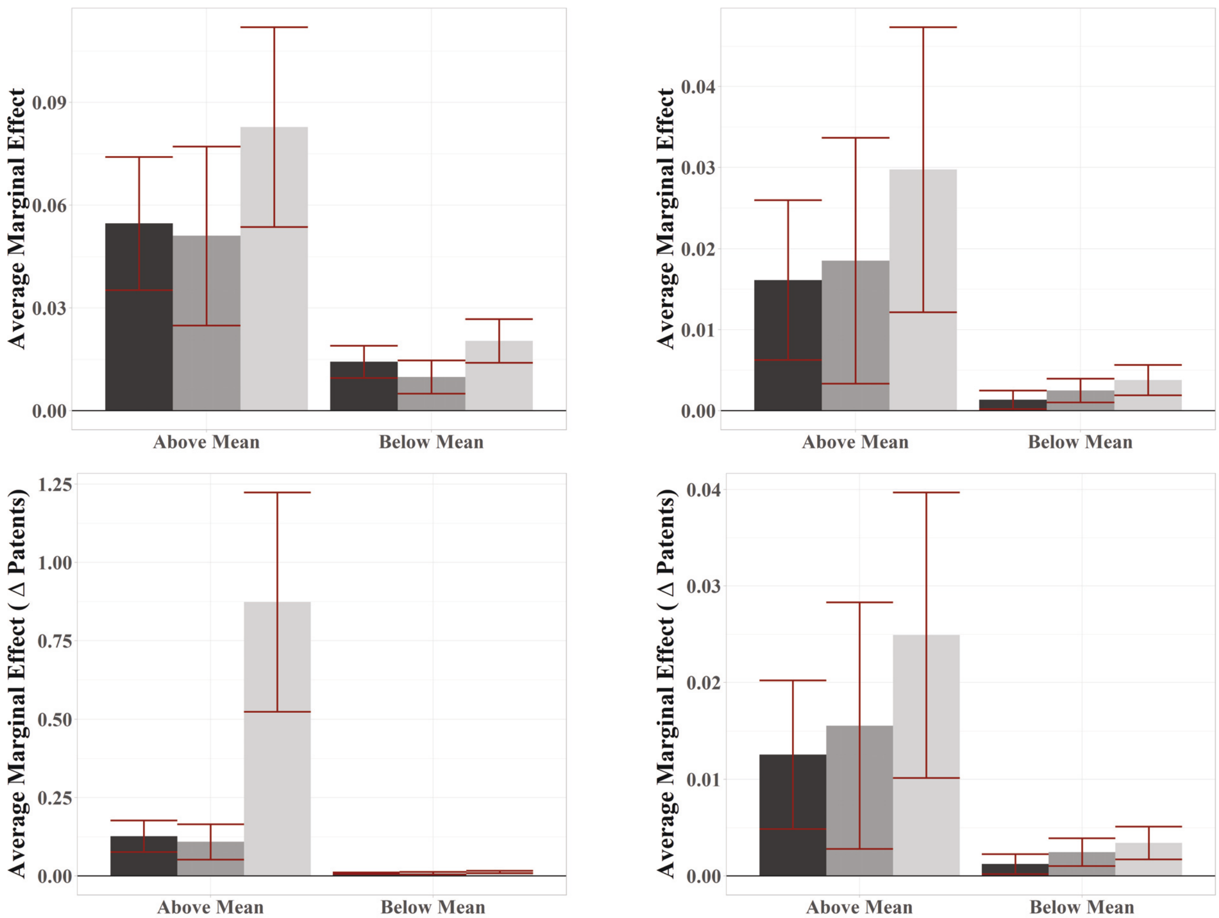
(e) $mig.\ dom = f(exp)$



(f) $mig.\ dom = f(lag_{t-15}(exp))$

Figure B.3: Dynamic Treatment Effects of Reforms on MNE Migrant Patents, No Cutoffs

Notes: The figure displays the coefficients and confidence intervals of $r_{ct} \times exp_{fct}$ in regressions of MNE migrant patents. The left column displays simple OLS regression with contemporaneous exposure, while the right column displays reduced form results with historic exposure. The first row corresponds to total patents, the second row GCPs, and the third row DOMs. Whiskers reflect 95% confidence intervals for point estimates. Cutoff coefficients are omitted from estimation.



(a) All Patents **(b)** Migrant Inv. Patents

Figure B.4: Average Marginal Effects of Reforms by Time-Varying MNE Size

Notes: The figure displays the difference in average marginal effects (in patents produced) between MNE subsidiaries with above and below yearly mean size (proxied for by the lagged mean of 10-year total patent volume during) based on segmented regressions of equation 2.1 (N. Obs 'Above Mean' = 149,803; N. Obs 'Below Mean' = 211,649). Dark grey bars correspond to predicted change in DOMs, medium grey bars to GCPs, and light grey bars to total patents. Whiskers reflect 95% confidence intervals for point estimates. The top row displays the average marginal effect in terms of log differences and the bottom row displays the marginal effect in terms of difference in patents.

Appendix C

Appendix to Chapter 3

C.1 An Example Proposal from the Experiment

Figure C.1 shows one of the early-stage grant proposals submissions received as part of the experiment. The proposal follows a standardized format emphasizing brevity and clarity, with the submission format designed to mask the identity of the submitting individual.

C.2 An Example PubMed Publication

Figure C.2 provides an example publication from the National Library of Medicine's Medline/PubMed database.[1] As can be seen in the image, the database includes a series of 'MeSH Terms' assigned to the publications by trained NLM librarians and drawn from the MeSH Knowledge taxonomy, which is useful for classifying biomedical knowledge. In the classification system, words following a '/' indicate modifier terms, which denote a specialized focus for the publication relative to that MeSH term, and words followed by '*' indicate that the MeSH term is a major focus of the publication. In the present study, I aggregate information on MeSH terms assigned to publications while discarding modifier and major-focus identifiers. Additionally, commonly used 'check tag' terms are discarded when the MeSH data are collected.[2]

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[1] Accessible at `https://www.ncbi.nlm.nih.gov/pubmed`.

[2] For the list of check tags, see `https://www.nlm.nih.gov/bsd/indexing/training/CHK_010.html`. That website can also be used more broadly to understand the process for classifying articles according to their MeSH terms.

SUBMISSION: #30

Genetic bases of the onset age variation in type 1 diabetes

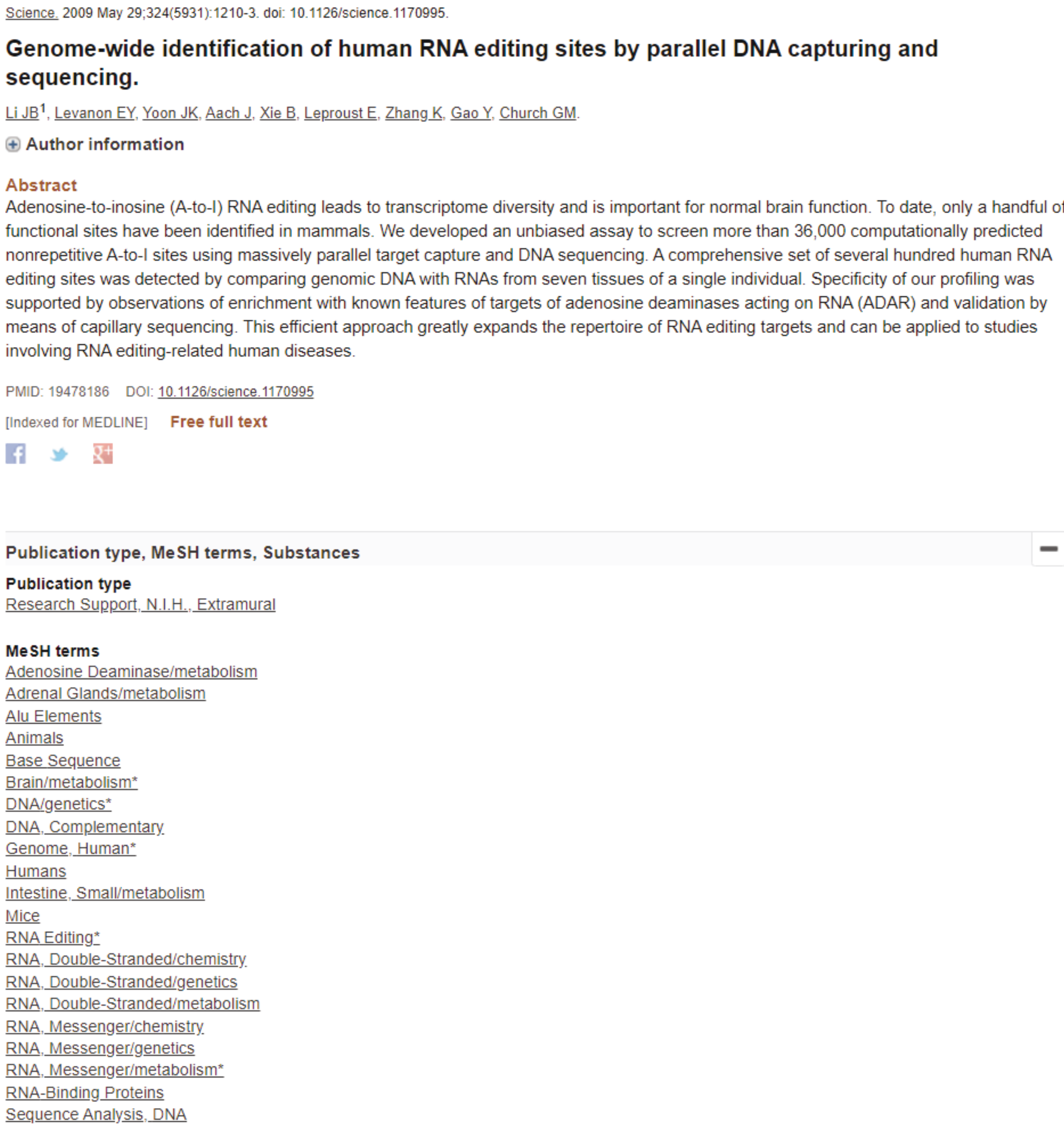
This proposal asks for genetic factors that contribute to the huge variability in the age at onset for type 1 diabetes. Type 1 diabetes usually affects younger individuals. In the United States, the peak age at diagnosis is around 14. However, significant number of patients may be diagnosed as type 1 diabetes after age 35. This type of diabetes is named latent autoimmune diabetes of adults (LADA). Due to the late age at onset, it is estimated that 20% of the patient with a type 2 diabetes diagnosis may in fact be type 1diabetes.

The age at onset difference between slow onset type 1 diabetes and acute diabetes is interesting but ignored. Genetic studies showed that LADA patients share some genetic features with type 1 diabetes. However, an important but largely ignored question is the genetic difference between juvenile type 1 diabetes and LADA patients bearing the same known T1D susceptible allele. Current programs identifying the shared susceptible alleles between juvenile T1D and LADA only confirm the classification of LADA as insulin dependent diabetes, but ignore the wealth of information these patients may present. It is not exciting enough to be able to manage a 40-year-old's diabetes the way we manage a 15-year-old. Yet, people will be thrilled if we can delay everyone's disease onset by 40 years. According to previous research, LADA patients also present higher allele frequency for T1D associated alleles such as HLA-DQB1 or INS VNTR, however, it is not clear whether these known T1D associated alleles are the major contributing factors for LADA etiology or other hidden genetic factors are playing a more determining role in the disease onset.

Detailed comparative genetic analysis on patients with similar T1D associated alleles (HLA or INS) but drastically different onset age will lead to novel insight in the etiology and prevention of T1D. We will be able to answer the following questions. A) Which key genetic mutations are linked to early age at onset when patients carry known T1D associated alleles? B) Whether age at onset can be further delayed by manipulating certain proteins. C) Whether age at onset is a function of the number of T1D associated alleles? Namely, patient bearing more disease alleles will have earlier onset. If so, which genes have additive effects? D) The significance of non-genetic factors in determining disease onset.

The detailed comparative genetic analysis is not performed partly because a lot of LADA patients are classified as type 2 diabetes patients, rendering the LADA patient pool relatively small. Also, cost efficient high density genomics tests are not accessible to many labs yet, and theoretical genetics models have not been developed to tackle this problem. However, with the progress of next generation sequencing technology, high statistical power can be obtained by using smaller patient sets and targeting less frequent alleles. Ideally, full genome sequencing of only two carefully matched (race, age, environment, life style, etc) patient pairs will yield meaning information. Novel susceptible genes identified will be meaningful target genes for future T1D research.

Figure C.1: An Example Proposal Submitted to the Grant Review Experiment



Science. 2009 May 29;324(5931):1210-3. doi: 10.1126/science.1170995.

Genome-wide identification of human RNA editing sites by parallel DNA capturing and sequencing.

Li JB[1], Levanon EY, Yoon JK, Aach J, Xie B, Leproust E, Zhang K, Gao Y, Church GM.

Author information

Abstract

Adenosine-to-inosine (A-to-I) RNA editing leads to transcriptome diversity and is important for normal brain function. To date, only a handful of functional sites have been identified in mammals. We developed an unbiased assay to screen more than 36,000 computationally predicted nonrepetitive A-to-I sites using massively parallel target capture and DNA sequencing. A comprehensive set of several hundred human RNA editing sites was detected by comparing genomic DNA with RNAs from seven tissues of a single individual. Specificity of our profiling was supported by observations of enrichment with known features of targets of adenosine deaminases acting on RNA (ADAR) and validation by means of capillary sequencing. This efficient approach greatly expands the repertoire of RNA editing targets and can be applied to studies involving RNA editing-related human diseases.

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Publication type, MeSH terms, Substances

Publication type

Research Support, N.I.H., Extramural

MeSH terms

Adenosine Deaminase/metabolism
Adrenal Glands/metabolism
Alu Elements
Animals
Base Sequence
Brain/metabolism*
DNA/genetics*
DNA, Complementary
Genome, Human*
Humans
Intestine, Small/metabolism
Mice
RNA Editing*
RNA, Double-Stranded/chemistry
RNA, Double-Stranded/genetics
RNA, Double-Stranded/metabolism
RNA, Messenger/chemistry
RNA, Messenger/genetics
RNA, Messenger/metabolism*
RNA-Binding Proteins
Sequence Analysis, DNA

Figure C.2: An Example PubMed Publication with MeSH Terms