11-4-2022

A Patent-Based Approach to Understanding the Role of University, Company, and Government Collaboration in Biotechnological Innovation

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by

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A Thesis Submitted in Partial Fulfillment of the Requirements for the Degree of Master of Science in Science, Technology, and Public Policy

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November 4, 2022

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ABSTRACT

The biotechnology industry has shifted in recent years in corporate policy from a more traditional, closed research and development (R&D) model to an open innovation (OI) model, leading to increased collaboration between companies and academic institutions. The literature has reinforced this shift by demonstrating the role these collaborative relationships play in contributing to high-quality innovations. In this study, I use a unique dataset composed of biotechnology patents granted in the United States from 2000-2020 to examine the relationship between patent assignee and patent quality. Specifically, I measure patent quality using the number of forward citations and patent family size and classify the biotech patents based on the number and type of their assignees (companies, government, or academic institutions). Multiple assignees—indicating the presence of collaborative behavior to produce the invention—are shown to have, in general, higher patent quality as opposed to patents with a single assignee. Patents produced by multiple companies, university-company, and university-company-government collaborations receive a higher number of forward citations relative to patents produced by a single company assignee. Also, simple patent family size is larger for patents produced by company-company collaborations as opposed to patents with a single assignee. Overall, the results support the hypothesis that cross-organizational collaborations—particularly company-company, university-company, and university-company-government collaborations—are associated with higher quality innovations in the biotechnology field, although these effects are stronger when considering number of forward citations rather than patent family size as a proxy for patent quality.

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1 INTRODUCTION

The biotechnology industry has shifted in recent years in corporate policy from a more traditional, closed research and development (R&D) model to an open innovation (OI) model, leading to increased collaboration between companies and academic institutions (Nilsson & Felding, 2015). The literature has reinforced this shift by demonstrating the role of these collaborative relationships in contributing to high-quality innovations (Kumaramangalam, 2005; Takabe et al., 2018; Kneller, 2010; Lincker et al., 2014; Patridge et al., 2015; Schuhmacher et al., 2018; Minguillo & Thelwall, 2015). The biotechnology industry serves as an excellent case to examine the impact of cross-organizational collaboration and OI on innovation quality due to its high R&D spending relative to other industries and the historically closed nature of biotechnology companies' R&D models.

Industry-academia collaboration plays a critical role in the success of high-technology industries such as biotechnology. The knowledge-sharing and learning gains attained in these collaborations support the generation of high-quality inventions. A high proportion of scientific specialists reside in academia, and these academic researchers benefit industry through collaborations by contributing their expertise to problem-solving (Kumaramangalam, 2005). The respective roles of academia and industry are illustrated clearly through a consideration of the drug discovery, development, and commercialization process. In the drug discovery sphere, university involvement is beneficial in that basic research and early development is a strength of academia. In addition, because academic researchers tend to pursue higher-risk novel drug targets than industry researchers can afford to do, academic research is a key contributor to industry pursuing the development of a greater number of drugs with novel mechanisms of action (Takabe et al., 2018 & Kneller, 2010). In turn, companies provide pharmaceutical and

commercial expertise that enable the translation of these drugs from an academic setting to a commercial one. Government often plays a key role in providing early funding that spurs innovation, especially for emerging technologies. The interactions between these three contributors—academia, industry, and government—in innovation are modeled through the "Triple Helix" (Hudson & Khazragui, 2013).

My study takes a patent-based approach, capable of accounting for the direct contributions of universities, companies, and governments, to assessing innovation quality in the biotechnology field by examining a dataset of patents derived from the Lens, including patents granted in the United States from 2000-2020 that are classified as biotechnology-related according to the International Patent Classification (IPC) system. The relationship between patent assignee and patent quality—here, proxied by number of forward citations and patent family size—is examined via regression analysis. Patent quality is a common indicator of the technological value of innovation. In patenting, there may be either a single or multiple assignees for a given patent; multiple assignees listed on a patent indicates a situation in which the rights to the patent are inclusive of all assignees and therefore suggests that collaborative relationships exist between the listed assignees. Patents with multiple assignees are shown to have, in general, higher patent quality as opposed to patents with a single assignee. Delving further in the organizations contributing towards these multiple-assignee patents, the results also support the hypothesis that cross-organizational collaborations—particularly company-company, university-company, and university-company-government collaborations—are associated with higher quality innovations in the biotechnology field, although these effects are stronger when considering number of forward citations as a proxy for patent quality than for patent family size.

While other researchers (Kumaramangalam, 2005; Takabe et al., 2018; Kneller, 2010; Lincker et al., 2014; Patridge et al., 2015; Schuhmacher, et al., 2018; Minguillo & Thelwall, 2015) have examined the role of collaborations between academic and industry partners in promoting innovation in biotechnology, this relationship has not been well-characterized using patent data; through this research, I seek to fill that literature gap and expand upon the existing literature by providing empirical evidence of the impact of cross-organizational collaboration on technological innovations. I expect this research to be beneficial in contributing toward the body of work guiding policymakers' decisions regarding optimization of its R&D funding patterns for maximized success of biotechnological innovation and potential incentivization of industry-academia collaborations through funding and patent policy.

2 LITERATURE REVIEW

2.1 THE TRIPLE HELIX MODEL: ROLES OF GOVERNMENT, COMPANIES, AND UNIVERSITIES IN INNOVATION

2.1.1 Interplay between Government, Private Industry, and Academia Stakeholders

For the purposes of examining biotechnological innovation from a public policy perspective, the Triple Helix model, which emphasizes the interactions between the three primary stakeholders in R&D and innovation policy—(1) universities, (2) private industry, and (3) federal government—is ideal (Hudson & Khazragui, 2013). The guiding principle of the Triple Helix concept is that "arrangements and networks among the Triple Helix institutional spheres provide the source of innovation rather than any single driver" (Etzkowitz, 2003).

The roles played by the three institutions included in the Triple Helix are related to but distinct from the roles which are traditionally attributed to each. Universities are becoming increasingly entrepreneurial, retaining their traditional role as producers of knowledge as a

public good but taking on a new role in promoting innovation as well (Etzkowitz, 2003). On the other hand, private firms are adopting models increasingly similar to the traditional academic model, with high levels of training and knowledge sharing, such that the process of innovation is no longer simply an internal one but one that takes place between firms and knowledge-producing institutions (Etzkowitz, 2003).

Government continues to serve in its traditional policy-making role, but increasingly interacts with the other players in the Triple Helix through economic and industrial policies. Specific government roles include not only funding R&D through both national labs and grants and subsidies to corporations and universities, but also mediating the conflict between intellectual property (IP) management on the part of the industry partner and the drive to publish on the part of the academic partner: the conflict between the public and private good aspects of technology. Government creates stronger incentives for collaboration between industry and academia through the adoption of legal frameworks that clearly define ownership of IP rights in the products of government-funded research. Further, the government is responsible for outlining a framework so that those IP rights can be transferred from public institutions to the private sector. Government policies such as the Bayh Dole Act, or the Patent and Trademark Act Amendments of 1980, enable universities, nonprofit research institutions, and small businesses to own, patent and commercialize inventions developed under federally funded research programs within their organizations (Portilla & Rohrbaugh, 2014).

2.1.2 Biotechnology and Pharmaceutical Innovation as a Case Study of the Triple Helix Model in Action

2.1.2.1 Shifting Roles of Industry and Academia: Open Innovation Corporate Policy

Biotechnology serves as an excellent case study of how the new Triple Helix structure of closer collaborations and interactions between private industry, academic institutions, and

government is transforming basic research into successful innovation. The pharmaceutical industry, which tends to overlap significantly with biotechnology, is a very apt selection for study simply in terms of its large volume of R&D spending relative to other industries. In a 2021 report by the Congressional Budget Office (CBO) on "Research and Development in the Pharmaceutical Industry", the "R&D intensity"—R&D spending as a share of net revenues (sales less expenses and rebates)—of the pharmaceutical industry was found to be over 25% in 2019 (averaging about 19% from 2000 to 2019) in contrast to the other industries studied (the Technological Hardware, Software, and Semiconductor industries), which each had an R&D intensity of less than 17% in 2019. For contrast, the Semiconductor industry, another research-intensive industry, had an average R&D intensity of only about 15% from 2000 to 2019 (CBO, 2021).

Traditionally, the pharmaceutical and biotechnology industries relied on a closed model of innovation, which was founded on the need for complete confidentiality and protection of IP (Nilsson & Felding, 2015). Since the 1990s, these industries' corporate policies have been shifting through necessity to a more OI model of R&D. The concept of "open innovation" was first coined by Dr. Henry Chesbrough of Harvard Business School in 2003 in his book, "Open innovation: The new imperative for creating and profiting from technology." Chesbrough describes a "paradigm shift" from the old paradigm, what he calls Closed Innovation, which contends that "successful innovation requires control," to the new paradigm of OI. The paradigm of closed innovation is that successful innovation requires control and ownership of IP. This system is historically founded in the early 1900s, when universities and governments were not involved in commercialization of science, leading to a need for companies to perform all R&D in-house at internal R&D units in order to be self-sufficient. On the other hand, the OI paradigm

is that companies benefit from use of external ideas in addition to internal ones. Notably, in his 2003 book, Chesbrough cited the pharmaceutical and biotechnology industries as examples of industries that were "in transition between the two paradigms" (Chesbrough, 2003).

From an industry perspective, the shift from closed to OI models may be attributed to a variety of factors, including the expiration of patents for many of the pharmaceutical industry's blockbuster drugs. Perhaps the most important driving factor is the high-cost burden and declining productivity of R&D. The efficiency of pharmaceutical R&D, as defined by the number of New Drug Applications (NDAs) submitted to the United States Food and Drug Administration (FDA) per billion U.S. dollars spent, has reportedly halved roughly every nine years for the past several decades (Reichman,& Simpson, 2016). Industry also benefits from interactions with universities in that academia provides highly-trained researchers and research managers to industry, and serves as an efficient and inexpensive process for screening talent (Hall & Rosenberg, 2010). Further, universities provide companies with open access to new information regarding research methods and findings, enabling businesses to identify and monitor scientific advances that have the potential to transform technologies and markets (Hall & Rosenberg, 2010).

From the academic perspective, steady declines in National Institutes of Health (NIH) funding have driven academic researchers to search for other sources of funding. Also, partnerships with industry may equip university scientists with new and advanced tools and instruments (Hall & Rosenberg, 2010). Thus, while the traditional paradigm is that federally-funded research enables early basic science research in academia such that this knowledge may be transferred to industry where biotechnological inventions are developed and commercialized, this paradigm is changing with increasingly OI-oriented policies.

2.1.2.2 The Role of Government: Relevant Federal Agencies (NIH, National Science Foundation (NSF), and FDA)

While viewing drug innovation from an OI perspective is logical in the context of corporate policy and the relationship specifically between academia and industry, the essential role of the third player in the Triple Helix—the government—in biotechnological innovation should not be neglected. The role of early federal funding in spurring innovation, especially for emerging technologies, is not to be understated. Tassey notes that "several decades of large-scale funding of molecular biology research by the NIH were required before private investment kicked in and spawned a biotechnology industry" (2004). Tassey goes so far as to attribute the creation of a biotechnology research infrastructure in both universities and industry to NIH funding, and the NIH Office of Extramural Research is, in fact, the largest funder of biomedical research in the world (NIH, 2019). Cleary et al., showed that NIH funding contributed to research publications associated with every one of the 210 new drugs approved by the FDA between 2010 and 2016 (2018).

Aside from the NIH, the other major federal funder in the drug innovation space is the NSF, which funds about 20% of all federally-supported basic research conducted at universities in the U.S. (NSF, n.d.). As mentioned earlier, the government also continues to serve in its regulatory role through the FDA, which approves drugs for marketing in the United States following review of the drugs' effects by the FDA's Center for Drug Evaluation and Research (CDER) (US Food & Drug Administration, 2022). The federal government also continues to influence university-industry relationships, technology transfer, and patent law through its innovation policies.

2.1.2.3 Forms of Collaboration between Industry, Academia, and Government

Primary forms of collaboration between the biotechnology and pharmaceutical industries and academic or government institutions include public-private partnerships (PPPs), academic centers of excellence, and direct collaboration. The first form of collaboration, public-private partnership, in which participants exchange data, share expertise, resources, IP, and ultimately risk, is commonly applied to enabling drug development for neglected diseases. By definition, a public-private partnership is an arrangement between a government institution—which provides funding for the project—and other institutions such as universities or companies. Examples include the Drugs for Neglected Diseases Initiative (DNDi) and the Medicines for Malaria Venture (MMV), which are sponsored by a variety of universities, research centers, governmental organizations, biotech companies, and pharmaceutical companies (Tralau-Stewart et al., 2009). The second type of collaboration is academic centers of excellence or innovation centers, established by companies to leverage the expertise of academic research institutions. Pfizer's Global Centers for Therapeutic Innovation (CTIs) in partnership with the University of California at San Francisco serves as an excellent example (Schuhmacher, et al., 2018) of this collaboration form. Another instance is the Genomics Institute of the Novartis Research Foundation (GNF), which is affiliated with academic centers such as the Scripps Research Institute, the University of California at San Diego, and the Salk Institute for Biological Studies (Thomas & McKew, 2014). The third type of collaboration is "direct" collaboration between pharmaceutical or biotechnology companies and academic institutions. Examples of prominent universities known to collaborate in this way include Harvard—with collaborations with Ipsen, Pfizer, Roche, and Sanofi—and Vanderbilt—with collaborations with GlaxoSmithKline, Janssen, Bristol-Myers Squibb, and AstraZeneca (Thomas & McKew, 2014). These "direct" collaborations stem from companies seeking to leverage an academic institution's expertise in

exchange for funding. Stepping into their new entrepreneurial role described above, universities are also beginning to take their involvement in the drug discovery and development process further down the innovation chain, particularly through spinout companies, which represent the translation of publicly-funded research into private entrepreneurial endeavors (Hudson & Khazragui, 2013).

2.2 COLLABORATION BETWEEN UNIVERSITIES AND COMPANIES IN BIOTECHNOLOGY

In cross-organizational collaboration, the academic partner provides knowledge sharing, access to scientific expertise, and a focus on basic research; companies, in turn, provide commercial expertise enabling the translation of early discoveries into commercial products. One of the most common appearances of academic-industry collaboration in biotechnology in the literature is in the form of studies exploring the relative contributions of these two parties as originators of new drugs. Some researchers, including Takabe et al. (2018), have investigated industry-academia collaborations from the academic contributor's perspective. Takebe et al. (2018) investigate the success rates of nearly 800 drug discovery projects conducted between 1991 and 2015 at 36 academic institutions in the U.S. for the various phases of clinical trials and the approval process—phase I, II, III, and NDA or Biologics License Application (BLA)—and compare these rates to those of the pharmaceutical industry. The study finds that the rates were similar for academia and the industry, and that collaboration plays an essential role in bringing the academic-origin drugs to the phase III and NDA/BLA stages; all projects that were successful at these later stages were found to involve academic-industrial collaboration. This study also takes into account the effect of disease domain and modality on the success rate of the collaboration.

Further, Kneller (2010) demonstrates that, out of a dataset of 252 new drugs approved by the FDA between 1998 and 2007, 24% originated from a university. Lincker et al. (2014) use prior patent art to demonstrate that, out of 357 FDA-approved drugs, 48% originated from academic research. Finally, Patridge, et al., (2015) show that 55% of 1453 FDA-approved new molecular entities (NMEs) were first reported in academia.

Taking a different approach, Schuhmacher et al. (2018) consider the financial benefits of collaboration from the industry partner's perspective. The authors, in an analysis of the key financial and R&D figures of multinational pharmaceutical companies, find that the industry R&D standard comprises a project portfolio with approximately 50% externally generated R&D and predominantly introverted innovation management. Further, companies with a proportion of externally acquired R&D projects that is above benchmark were found to have a higher Earning Before Tax and Interest (EBIT) margin and an average stock price that increased continuously by 5-10% higher in 2006 to 2011 compared with companies that acquired less than 50% of their projects from the outside.

Other, non-drug-related studies have also explored the importance of university-industry collaboration in contributing towards high-quality biotechnology outputs. These sometimes make use of scientific publications as a method of studying collaboration between private and academic researchers; co-authorship is considered a "form of direct interaction and knowledge transfer between the communities" (Minguillo & Thelwall, 2015). For instance, Kumaramangalam (2005) uses a dataset of scientific articles from the United Kingdom's (U.K.) biotechnology sector from 1988 to 2001 to show that increased academic contribution on industry research papers improves research quality, as proxied by journal status.

2.3 PRECEDENT FOR PATENT-BASED ASSESSMENT OF INNOVATION QUALITY

In this study, I use patent data to measure the innovation. Historically, measures of innovation have evolved from early input measures such as R&D expenditure and number of scientists to output measures such as patent counts, publications, or licensing (Donoso, 2017). Today, patents are the main source of data on innovation. Patenting involves an inventor paying a fixed cost in exchange for earning a legal monopoly right over an invention. The rationale behind patents as measure of innovation is that, in theory, all innovations that are profitable—those for which the monopoly profits over the duration of the patent exceed the fixed cost of the patent—should be patented (Donoso, 2017).

Patent "quality" has been widely utilized to represent the innovativeness, impactfulness, and "technological value of an invention" (Michelino, et al., 2016) in the literature. Various indicators of patent quality have been explored, including forward citations, backward citations, number of claims, family size, generality, and originality (Baron & Delcamp, 2012). One of the most common indicators of patent quality is number of forward citations, defined as the number of patent applications that cite the patent of interest as an influential "prior art" (Briggs & Wade, 2014). Lanjouw and Schankerman (2004) suggest that the forward citations are the most important quality indicator for drug patents. Forward citations generally indicate the relevance and influence of the patent for future research and innovations (Baron & Delcamp, 2012) and capture the importance of the innovation in facilitating "spillovers", the development of public knowledge, and cumulative innovation (Briggs & Wade, 2014; Sterzi, 2013). Forward citations are also thought to be a useful indicator given that they are forward-looking rather than driven by any strategic behavior on the part of the applicant, as is the case with indicators such as number of claims or backward citations (Sterzi, 2013). Many studies have demonstrated that forward

citations are highly correlated with innovation value, from the perspective of both technological impact and market and social value (Briggs, 2021).

In one example of a study employing the number of forward citations as an indicator of patent quality, Sterzi (2013) examines the relationship between ownership structure and patent quality, indicated by number of forward citations, for both university-owned and corporate-owned patents in the U.K. from 1990-2001. Sterzi (2013) finds that academic patents owned by companies receive more citations in the first years after the filing date than those owned by universities or other public research organizations when controlling for observable inventor and patent characteristics. Additionally, patent quality is higher for patents originally assigned to universities but transferred to companies, showing the importance of translation from academia to industry. In another study, examining university-industry collaborations of Italian inventors from 1978-2007, Crescenzi et al. (2017) measure patent quality via forward citations. They find that university-industry collaborations are less likely to occur than collaborations between exclusively university partners or business partners, but that these collaborations tend to generate patents with high general applicability and patent quality as proxied by forward citations. Also, Briggs and Wade (2014) find that joint patent ownership positively impacts the quality of an innovation, as measured by forward patent citations.

A second commonly used indicator of patent quality is family size, which is defined as the number of international patents filed for the same priority patent (Baron & Delcamp, 2012). Patent family size is relevant as an indicator of quality in that it indicates that a patent is important on an international scale. Further, if the patent's assignee is willing to incur the high application costs necessary to obtain patents internationally (Baron & Delcamp, 2012), it follows

that the assignee expects the patent to prove profitable enough to defray and potentially exceed those costs.

Ocean Tomo is a platform that offers periodical auctions in which patents are sold by individual inventors or investors, academic institutions, companies, and government agencies, allowing researchers to have a direct measure of the private value of a patent. Using Ocean Tomo's auction data to empirically test predictions on patent value indicators on real-world auction prices, Fischer and Leidinger (2014) find support for both forward citations and patent family size as indicators of patent value. Guellec & van Pottelsberghe de la Potterie (2000), however, find that, family size is only correlated to patent value up to a certain threshold. They conjecture that, for many technologies, protection in only a few countries, especially if these are large ones, may be sufficient to gain worldwide protection without incurring the cost of patenting in additional smaller countries (Guellec & van Pottelsberghe de la Potterie, 2000). This may be a limitation to using patent family size as an indicator of patent quality.

3 METHODS

3.1 RAW DATA COLLECTION

I collected the patent data from the Lens structured patent search featuring data derived from the U.S. Patent and Trademark Office (USPTO)[1]. My objective was to obtain a dataset of patents classified under the 8th edition of the IPC system as falling in the biotechnology sector. The list of IPC codes used is derived from the OECD Science, Technology and Industry Scoreboard (2009): A01H1/00, A01H4/00, A61K38/00, A61K39/00, A61K48/00, C02F3/34, C07G(11/00, 13/00, 15/00), C07K(4/00, 14/00, 16/00, 17/00,19/00), C12M, C12N, C12P, C12Q,

[1] Data were retrieved from https://www.lens.org/lens/search/patent/structured in June, 2022

C12S, G01N27/327, G01N33/(53*, 54*, 55*, 57*, 68, 74, 76, 78, 88, 92) (*Table A1)*. In this analysis, I focus on the biotechnology patents that were granted in the U.S. between January 1st, 2000, and January 1st, 2020, and were classified with at least one of the above IPC codes (*Figure 1, Table A2).*

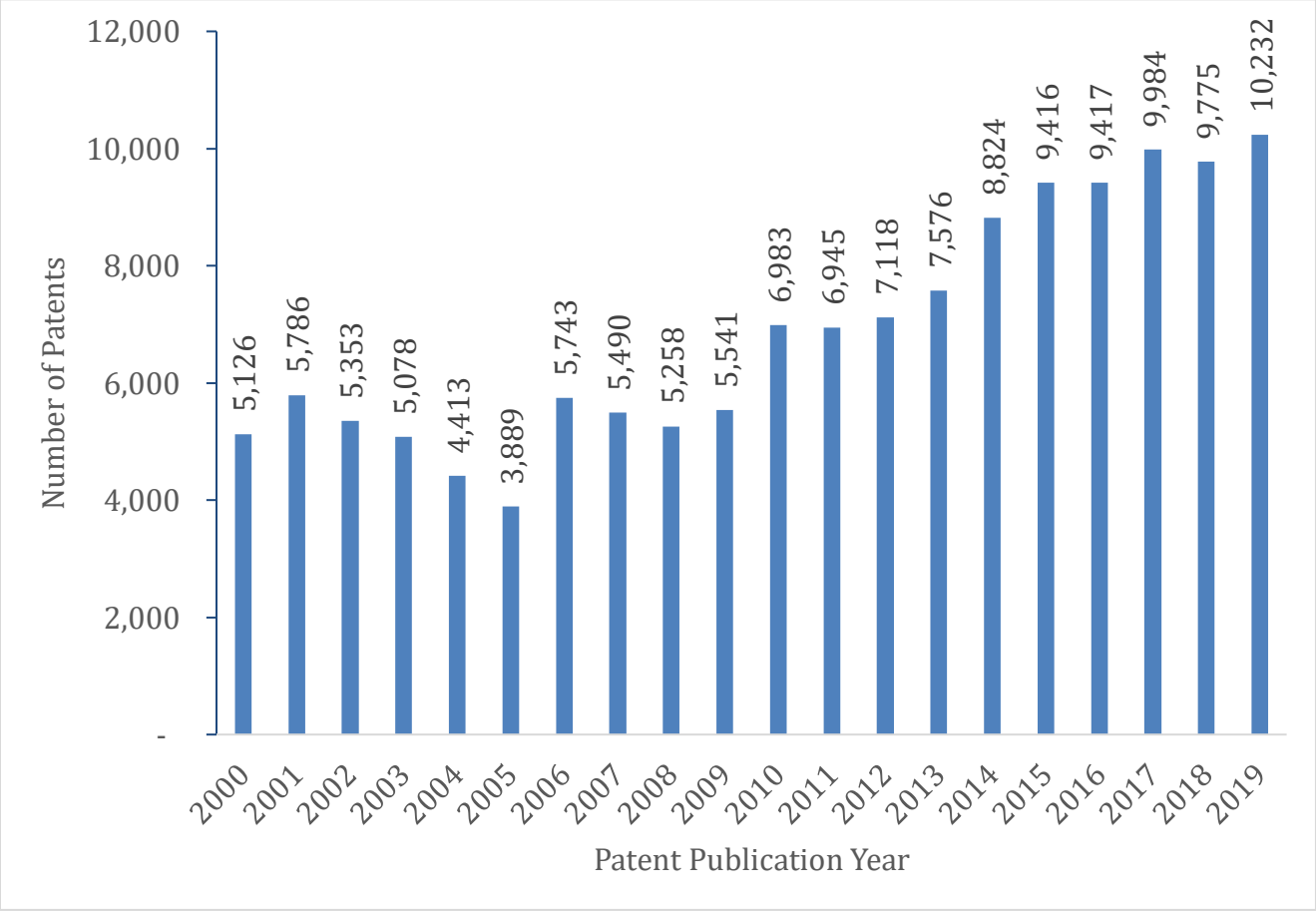

Figure 1: Number of Patents in the Dataset Published Each Year from 2000 to 2020

3.2 GENERATION OF FINAL DATASET FOR ANALYSIS

From the raw dataset obtained as described above, duplicate entries with the same patent family were dropped, ensuring that each observation represents one unique invention. Patents with no owner information available were also dropped. Finally, all patents for which the first assignee's country was not one of the assignee countries with at least 1000 patents were dropped.

This means that the final dataset only includes patents for which the first assignee's country is listed as the United States, Japan, Germany, Great Britain, France, Switzerland, Canada, Korea, the Netherlands, Denmark, Israel, China, Australia, Taiwan, Belgium, or Sweden (*Figure 2, Table A3)*, a list which captures the countries most prevalent on the U.S. patenting stage. The final dataset contains 137,947 total biotechnology patents. For 88,585 (64%) of these, the first listed assignee's country is the U.S..

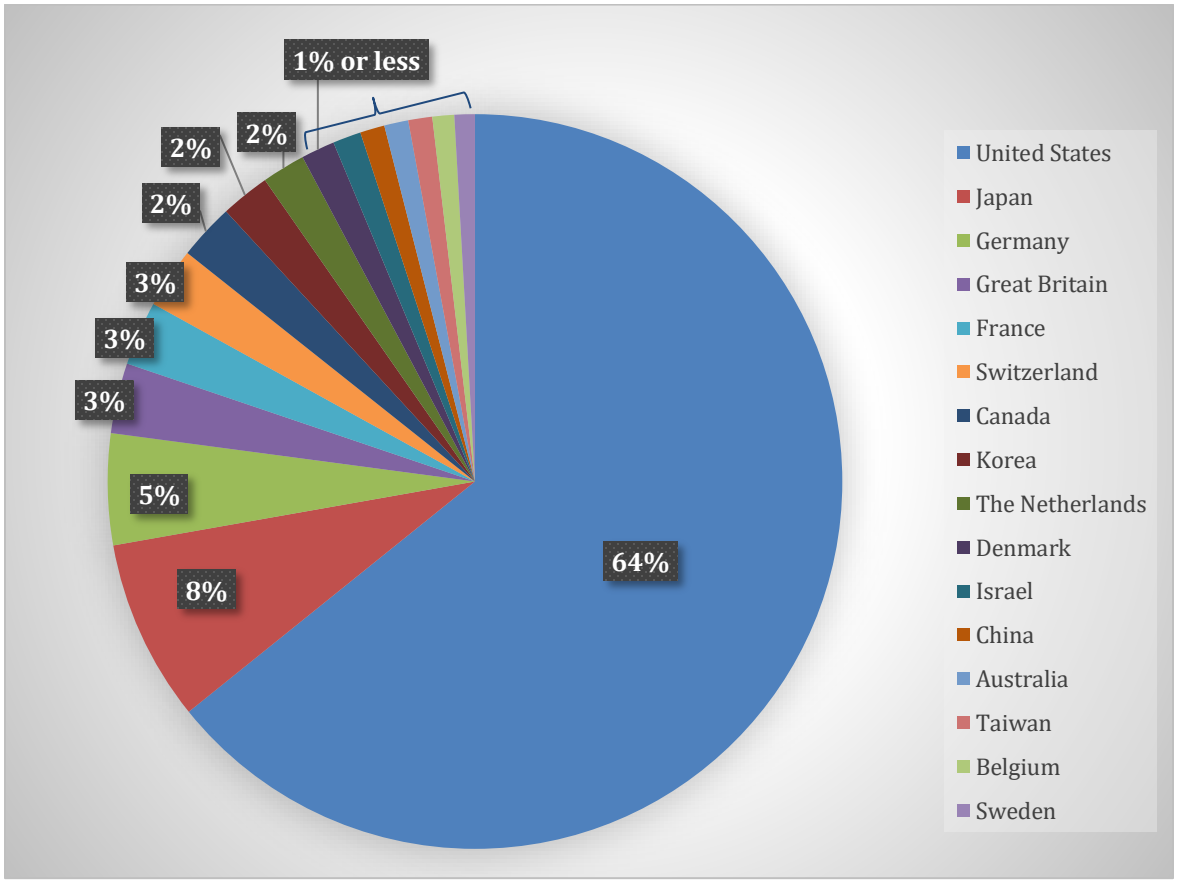

Figure 2: Frequency of Assignee Country in Dataset

The guidelines provided in the OECD Patent Statistics Manual (OECD, 2009) were used as a starting point for developing the script which was used to assign an organization type to each assignee based on keywords included in the assignee name. The four possible organization

types are: (1) university (including academic institutions and hospitals), (2) corporate organizations or companies (industry), (3) government (any government-affiliated institution, including the NIH), and (4) others (i.e., an assignee cannot be identified as any of the aforementioned organization types). Of the 137,947 patents included in my sample, 44,309 (about 32%) had multiple assignees, while the other 93,638 (about 68%) had single assignees, with the bulk of these being single companies (613,44 patents, or about 44%) (*Figure 3, Table A4)*. The distribution of assignee organization types for the U.S.-only sample population is fairly similar; of the 88,585 patents included in the U.S.-only dataset, 26,611 (about 30%) had multiple assignees, while the other 61,974 (about 70%) had single assignees, with the bulk of these being single companies (37,966 patents, or about 43%) (*Figure 4, Table A5)*.

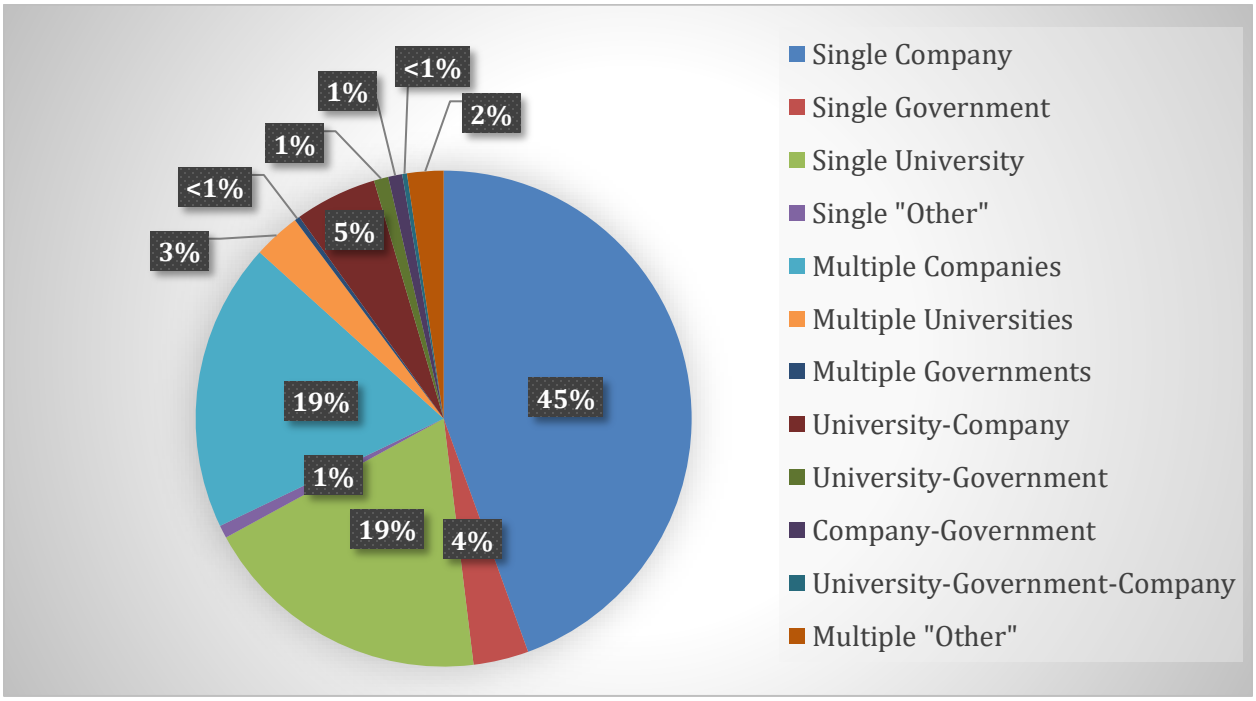

Figure 3: Frequency of Assignee Organization Types for Patents with First Listed Assignee from the United States, Japan, Germany, Great Britain, France, Switzerland, Canada, Korea, the Netherlands, Denmark, Israel, China, Australia, Taiwan, Belgium, or Sweden

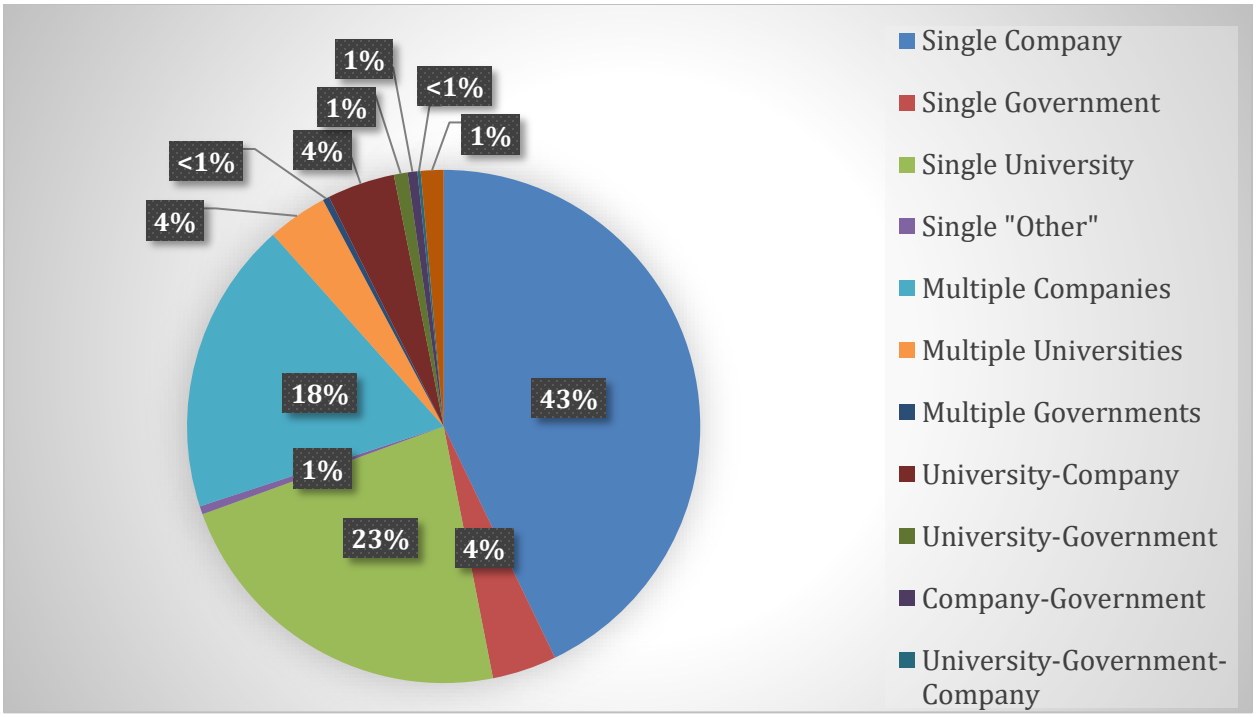

Figure 4: Frequency of Assignee Organization Types for Patents with First Listed Assignee from the U.S. Only

3.3 MEASURES IN THE MODEL

To measure the quality of a biotech patent, I use two outcome variables: the number of forward citations and the size of the patent family (*Table 1).* For the full 16-country sample, the number of forward citations ranges from 0 to 2,850, with a mean of 14 and a standard deviation of 45; the simple family size ranges from 1 to 391, with a mean of 15 and a standard deviation of 20.

Table 1: Summary Statistics for Dependent Variables

Variable	**Number of Observations**	**Mean**	**Standard Deviation**	**Minimum**	**Maximum**
Number of Forward Citations	137,947	14	45	0	2,850
Simple Family Size	137,947	15	20	1	391

My independent variables include the following:

Multiple Assignees: A binary variable was generated to indicate whether the patent had more than one assignee listed (single assignee is coded as zero; multiple assignees are coded as one). Single assignee refers to a situation in which the rights to the patent are exclusive and no collaboration behavior is considered to exist in the inventive process. On the other hand, multiple assignees refers to a situation in which the rights to the patent are inclusive of all assignees. Further, collaborative relationships are considered to exist between assignees listed on a multiple-assignee patent.

Assignee Organization Type: I constructed 12 binary variables to measure the collaboration among different types of patent assignees (first by identifying whether the number of assignees is single or multiple and then by identifying the organization category). These are mutually exclusive such that a single patent will have 0 for eleven of the variables but 1 for one of the variables. (1) The variable single company indicates whether a patent has a single assignee that is categorized as a company. (2) The variable single government indicates whether a patent has a single assignee that is categorized as a governmental organization. (3) The variable single university indicates whether a patent has a single assignee that is categorized as a university. (4) The variable single "other" indicates whether a patent has a single assignee that is categorized as other. (5) The variable multiple companies indicates whether a patent has multiple assignees that are each categorized as a company. (6) The variable multiple universities indicates whether a patent has multiple assignees that are each categorized as a university. (7) The variable multiple governments indicates whether a patent has multiple assignees that are each categorized as a government. (8) The variable university-company indicates whether a patent has multiple assignees including at least one university organization and one business organization. (9) The

variable university-government indicates whether a patent has multiple assignees, including at least one university organization and at least one assignee as government organization. (10) The variable company-government indicates whether a patent has multiple assignees, including at least one business organization and at least one government organization. (11) The variable university-government-company indicates whether a patent has multiple assignees, including at least one university organization, at least one government organization, and at least one business organization. Finally, (12) the variable multiple "other" indicates whether a patent has multiple assignees, with *any* of those assignees being categorized as other. Note that, for regressions against assignee organization type, single company assignee organization type was used as the baseline or omitted category.

In addition to the variables of interest, I also include the following additional independent variables to control for the differences in technological fields, countries of origin, and time of patent publication:

Number of IPC Codes: The number of IPC codes associated with each patent was identified and used to control for the generalness of each patent, such that a greater number of IPC codes associated with a patent is thought to indicate a greater level of generalness. For the full 16-country sample, number of IPC codes ranges from 1 to 169, with a mean of 7 and a standard deviation of 6 (*Table A6)*.

Assignee Country: A binary dummy variable was generated for the country of the first listed assignee (US, JP, DE, GB, FR, CH, CA, KR, NL, DK, IL, CN, AU, TW, BE, and SE). Note that, in the regressions, the U.S. is used as the baseline/omitted country.

Publication Year: A binary dummy variable was generated for each year (2000 through 2020) to control for the year the patent was published. This is particularly important in regressions against number of forward citations, as one of the primary limitations of utilizing forward citations as an indicator of patent quality is the issue of "time truncation", or the "natural bias that older patents likely have more citations because they have had more time to be cited" (Briggs & Wade, 2014). Note that, in the regressions, 2000 (the first year in the dataset) is used as the baseline/omitted year.

IPC Section Symbol: To control broadly for the type of technology a certain patent falls under, I use a set of binary variables each indicating one of the eight IPC sections (WIPO, 2022; *Table A1).* Based on the IPC system, a given patent may be categorized by one or more IPC codes and therefore may be associated with one or more of the eight IPC sections. In the full 16-country sample, 48% of patents were associated with a section A IPC code; 6% with section B; 81% with section C; 27% with section G; and 1% with section H (*Table A7).* Note that, in the regressions, IPC section C is used as the baseline/omitted IPC section symbol, as it has the highest frequency in the dataset.

4 ANALYSIS AND DISCUSSION

4.1 EFFECT OF MULTIPLE ASSIGNEES ON PATENT QUALITY

I begin by estimating a regression model (specified in *Equation 1*) to examine the correlation between patent quality and an indicator of multiple assignees, while controlling for number of IPC codes, assignee country, publication year, and IPC section symbol.

Equation 1: $Y_{ict} = \beta_1 * \text{multi\_assignee(i)} + \beta_2 * \text{number\_of\_IPC} + \gamma_c + \gamma_t + \delta_{ipc} + \varepsilon_{ict}$

In the model, the dependent variable Y is a proxy for patent quality, either number of forward citations or simple patent family size, of a patent i from country c published in year t. β_1 denotes the coefficient for the independent variable, multiple assignees. β_2 denotes the coefficient for a control variable, number of IPC codes. γ_c , γ_t, and δ_{ipc} denote sets of binary variables indicating assignee country, publication year, and IPC section symbol, respectively. Finally, ε_{ict} denotes the error term.

Table 2 reports my regression results. In columns 1 and 2, the dependent variable is the number of forward citations, while the dependent variable in columns 3 and 4 is the size of patent family. For both outcomes, I report the regression results based on the full sample (patents filed by assignees in 16 countries) and a restricted sample of patents by U.S. assignees only. First, in columns 1 and 2, I find that the estimated coefficients of the multiple assignee indicator are positive and statistically significant at the 1% level. More specifically, this suggests that a patent with multiple owners on average receives 4.0 more citations than a patent with one single assignee (column 1), when everything else is held constant. This difference is slighter larger for U.S.-based patents (column 2); a U.S.-based patent with multiple assignees on averages receives 4.9 more citations than a patent with one single assignee.

Notably, I include the number of IPC codes associated with each patent as a control for generalness and IPC section symbols as a control for the type of technology associated with a given patent. In column 1, I find that the estimated coefficient for the number of IPC codes is positive and statistically significant at the 1% level, suggesting that patents spanning more technological fields receive more citations. More specifically, my estimated coefficient indicates that a given patent on average receives 0.4 more forward citations for every additional IPC code associated with that patent. I also find that the estimated coefficients for IPC section symbols B,

F, G, and H are positive and statistically significant at the 1% level, suggesting that a given patent on average receives 6.1 more forward citations if it is associated with IPC section symbol B in comparison to IPC section symbol C; 5.2 more forward citations if it is associated with IPC section symbol F; 1.4 more forward citations if it is associated with IPC section symbol G; and 6.6 more forward citations if it is associated with IPC section symbol H. These effects are very similar for U.S.-based patents (column 2).

In columns 3 and 4, I show that the effect of multiple assignees on simple patent family size is also positive and statistically significant at a 1% level. More specifically, this suggests that the simple family size of a patent with multiple owners is on average 3.2 patents larger than that of a patent with one single assignee (column 3), when everything else is held constant. This difference is slighter larger for U.S.-based patents (column 4); the simple patent family size of a patent with multiple owners for a U.S.-based patent is on average 3.6 patents larger than that of a patent with one single assignee.

In column 3, I find that the estimated coefficient for the number of IPC codes is positive and statistically significant at the 1% level. More specifically, this suggests that the simple patent family size of a patent is on average 0.9 patents larger for every additional IPC code associated with that patent. I also find that the estimated coefficients for IPC section symbols A, D, E, and H are positive and statistically significant at the 1% level, suggesting that the simple patent family size of a patent is on average 0.7 patents larger if it is associated with IPC section symbol A in comparison to IPC section symbol C; 3.6 patents larger if it is associated with IPC section symbol D; 39.2 patents larger if it is associated with IPC section symbol E; and 1.3 patents larger if it is associated with IPC section symbol H. On the other hand, I find that the estimated coefficients for IPC section symbols B, F, and G are negative and statistically significant at the

1% level, suggesting that the simple patent family size of a patent is on average 1.0 patents smaller if it is associated with IPC section symbol B in comparison to IPC section symbol C; 4.1 patents smaller if it is associated with IPC section symbol F; and 0.6 patents smaller if it is associated with IPC section symbol G. For U.S.-based patents, the effects observed for number of IPC codes and IPC section symbols D through H are very similar for U.S.-based patents (column 4); however, the effect of IPC section symbol B is not statistically significant at the 1% level for U.S.-based patents. Additionally, I find that simple patent family size of a U.S.-based patent is on average 0.8 patents smaller if it is associated with IPC section symbol A, as opposed to 0.8 patents larger as observed in the 16-country dataset. Overall, these results suggest that an invention developed by multiple organizations (regardless of their type) tends to have higher quality compared to an invention developed by one single organization.

Table 2: Estimated Effect of Number of Assignees on Patent Quality (as Proxied by Number of Forward Citations and Simple Patent Family Size) of Biotechnology Patents from 2000 to 2020 in the United States

	Number of Forward Citations		**Simple Patent Family Size**	
	1	2	3	4
	US, JP, DE, GB, FR, CH, CA, KR, NL, DK, IL, CN, AU, TW, BE, SE	US only	US, JP, DE, GB, FR, CH, CA, KR, NL, DK, IL, CN, AU, TW, BE, SE	US only
Multiple Assignees	4.000*** (0.247)	4.946*** (0.357)	3.169*** (0.107)	3.630*** (0.143)
Number of IPC Codes	0.358*** (0.021)	0.423*** (0.030)	0.920*** (0.009)	1.031*** (0.012)
IPC Section Symbol A	-0.156 (0.259)	-0.523 (0.366)	0.741*** (0.112)	-0.761*** (0.147)

IPC Section Symbol B	6.148*** (0.510)	8.129*** (0.721)	-0.978*** (0.221)	-0.075 (0.289)
IPC Section Symbol D	-0.475 (1.706)	1.092 (2.570)	3.615*** (0.739)	7.942*** (1.031)
IPC Section Symbol E	-1.575 (3.896)	-5.197 (5.365)	39.215*** (1.687)	54.507*** (2.152)
IPC Section Symbol F	5.153*** (1.747)	5.004** (2.332)	-4.072*** (0.756)	-4.996*** (0.935)
IPC Section Symbol G	1.413*** (0.276)	1.815*** (0.392)	-0.586*** (0.119)	-0.589*** (0.157)
IPC Section Symbol H	6.588*** (1.062)	8.890*** (1.487)	1.281*** (0.460)	3.244*** (0.596)
Constant	42.073*** (0.625)	49.274*** (0.865)	1.789*** (0.271)	0.369 (0.347)
Observations	137,947	88,585	137,947	88,585
R-squared	0.102	0.109	0.112	0.124

Standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*
Note that the following variables were controlled for in these regressions (not shown in the table for brevity): Assignee Country and Publication Year.

4.2 Effect of Assignee Organization Type on Patent Quality

To further examine the effect of cross-organizational collaboration, I estimate another regression model with more detailed characterization of assignee organization type and their collaboration relationship, specified as *Equation 2*.

Equation 2: $Y_{ict} = \beta_1$*single_government(i) + β_2*single_university(i) + β_3*single_other(i) + β_4*multiple_companies(i) + β_5*multiple_universities(i) + β_6*multiple_governments(i) + β_7*university_company(i) + β_8*university_government(i) + β_9*company_government(i)+ β_{10}*university_government_company(i) + β_{11}*multiple_others(i) + β_{12}*number_of_IPC + γ_c + γ_t + δ_{ipc} + ε_{ict}

In this equation, the dependent variable Y is a proxy for patent quality, either number of forward citations or simple patent family size, of a patent i from country c published in year t. β_1 through β_{11} denote the coefficients for the independent variables of interest measuring various assignee organization types. β_2 denotes the coefficient for a control variable, number of IPC codes. γ_c , t, and δ_{ipc} denote sets of binary variables indicating assignee country, publication year, and IPC section symbol, respectively. Finally, ε_{ict} denotes the error term. I report the regression results in *Table 3.*

For both outcomes, I report the regression results based on the full sample (patents filed by assignees in 16 countries) and a restricted sample of patents by U.S. assignees only. Across all specifications, patents with a single company assignee are the omitted category. Thus, the estimated coefficients on the assignee organization variables indicate their difference from the omitted category.

First, in columns 1 and 2, I find that patents with single government, single university, and single "other" assignees receive significantly fewer citations compared to patents with one single corporate assignee. In column 1, I find that the estimated coefficients of the single government, single university, and single other assignees indicators are negative and statistically significant at the 1% level. More specifically, this suggests that a patent with a single

government assignee on average receives 5.0 fewer forward citations than a patent with one single corporate assignee; a patent with a single university assignee receives 1.5 fewer citations; and a patent with a single "other" assignee receives 5.0 fewer citations, when everything else is held constant (column 1). Similarly, for the U.S.-based patents (column 2), I find that a U.S.-based patent with a single government assignee on average receives 7.2 fewer forward citations than a patent with one single corporate assignee and a U.S.-based patent with a single university assignee receives 3.3 fewer citations. However, I find that the estimated coefficient for the single "other" assignees of U.S.-based patents is not statistically significant at the 1% level, although the estimated coefficient for multiple universities is, indicating that a U.S.-based patent with multiple universities assignees on average receives 2.6 fewer forward citations than a patent with one single corporate assignee.

On the other hand, I find that patents with multiple companies, university-company, and university-company-government assignees receive significantly *more* citations compared to patents with one single corporate assignee. In column 1, I find that the estimated coefficients of the multiple companies, university-company, and university-company-government indicators are positive and statistically significant at the 1% level. More specifically, this suggests that a patent with multiple company assignees on average receives 4.6 more forward citations than a patent with one single corporate assignee; a patent with university and company assignees receives 2.3 more citations; and a patent with university, company, and government assignees receives 17.0 more citations, when everything else is held constant (column 1). Similarly, for the U.S.-based patents (column 2), I find that a U.S.-based patent with multiple company assignees on average receives 4.7 more forward citations than a patent with one single corporate assignee; a U.S.-based patent with university and company assignees receives 3.4 more citations; and a U.S.-

based patent with university, company, and government assignees receives 35.1 more citations. I also find that the estimated coefficients of multiple "other" assignees is positive and statistically significant at the 1% level for U.S.-based patents, suggesting that a patent with multiple "other" assignees on average receives 4.3 more forward citations than a patent with one single corporate assignee.

In columns 3 and 4, I find that the simple patent family size for patents with single government, single university, single "other", multiple universities, multiple governments, and multiple "other" assignees is significantly smaller than that of patents with one single corporate assignee. In column 3, I find that the estimated coefficients of the single government, single university, single "other", multiple universities, university-government, and multiple "other" indicators are negative and statistically significant at the 1% level. More specifically, this suggests that the simple family size of a patent with a single government assignee is on average 3.8 patents smaller than that of a patent with one single corporate assignee; the simple family size of a patent with a single university assignee is on average 5.0 patents smaller; the simple family size of a patent with a single "other" assignee is on average 3.6 patents smaller; the simple family size of a patent with a multiple university assignees is on average 3.5 patents smaller; the simple family size of a patent with university and government assignees is on average 3.5 patents smaller; and the simple family size of a patent with multiple "other" assignees is on average 2.6 patents smaller, when everything else is held constant (column 3). These effects are very similar for U.S.-based patents (column 4). The simple family size of a U.S.-based patent with a single government assignee is on average 3.4 patents smaller than that of a patent with one single corporate assignee; the simple family size of a U.S.-based patent with a single university assignee is on average 4.5 patents smaller; the simple family size of a U.S.-

based patent with a single "other" assignee is on average 5.1 patents smaller; the simple family size of a U.S.-based patent with a multiple university assignees is on average 2.5 patents smaller; the simple family size of a U.S.-based patent with university and government assignees is on average 2.8 patents smaller; and the simple family size of a U.S.-based patent with multiple "other" assignees is on average 2.7 patents smaller, when everything else is held constant.

On the other hand, I find that the simple patent family size for patents with multiple company assignees is significantly larger than that of patents with one single corporate assignee. In column 3, I find that the estimated coefficient of the multiple company indicator is positive and statistically significant at the 1% level. More specifically, this suggests that a patent with multiple company assignees on average receives 3.8 more forward citations than a patent with one single corporate assignee (column 3). This effect is slightly larger for U.S.-based patents (column 4), such that a U.S.-based patent with multiple company assignees on average receives 3.9 more forward citations than a patent with one single corporate assignee, when everything else is held constant. Notably, I again include the number of IPC codes associated with each patent as a control for generalness and IPC section symbols as a control for the type of technology associated with a given patent. The estimated coefficients of the number of IPC codes and many of the IPC section symbols are statistically significant at the 1% level, similar to the findings in *Table 2*.

I conducted additional tests to compare the estimated coefficients using number of forward citations as the proxy for patent quality on the various assignee variables (using the lincom command in Stata). Comparing the estimated coefficients for the effect of assignee organization type being university-company-government versus multiple companies or university-company, I find that patents with multiple assignees including universities,

government, and companies receive, on average, 12.3 forward citations more than patents with multiple company assignees and about 14.7 forward citations more than patents with multiple assignees including companies and universities. Thus, collaboration among universities, companies, and government agencies tends to yield the highest-quality innovation. I also find that patents with multiple company assignees receive, on average, 2.4 forward citation more than patents with multiple assignees including universities and companies. This indicates that company-company collaboration yields the second-highest patent quality, followed by university-company collaborations.

Overall, these results suggest that an invention developed by multiple companies, university-company, and university-company-government assignees tends to have higher patent quality than an invention developed by a single corporate assignee when considering number of forward citations. When considering simple patent family size, the results suggest that only an invention developed by multiple company assignees tends to have higher patent quality than an invention developed by a single corporate assignee.

Table 3: Estimated Effect of Assignee Organization Type on Patent Quality (as Proxied by Number of Forward Citations and Simple Patent Family Size) of Biotechnology Patents from 2000 to 2020 in the United States

	Number of Forward Citations		**Simple Patent Family Size**	
	1	2	3	4
	US, JP, DE, GB, FR, CH, CA, KR, NL, DK, IL, CN, AU, TW, BE, SE	US only	US, JP, DE, GB, FR, CH, CA, KR, NL, DK, IL, CN, AU, TW, BE, SE	US only
Single Government	-5.043*** (0.630)	-7.283*** (0.844)	-3.795*** (0.271)	-3.424*** (0.337)
Single University	-1.466*** (0.316)	-3.262*** (0.424)	-4.999*** (0.136)	-4.514*** (0.169)

Single "Other"	-5.018*** (1.271)	-3.716 (2.274)	-3.599*** (0.546)	-5.117*** (0.907)
Multiple Companies	4.624*** (0.318)	4.653*** (0.455)	3.823*** (0.136)	3.914*** (0.182)
Multiple Universities	-0.505 (0.678)	-2.596*** (0.871)	-3.474*** (0.291)	-2.484*** (0.348)
Multiple Governments	-0.372 (1.967)	-2.010 (2.539)	-0.604 (0.845)	0.446 (1.013)
University-Company	2.255*** (0.526)	3.414*** (0.826)	-0.426* (0.226)	0.371 (0.329)
University-Government	0.274 (1.194)	-0.657 (1.758)	-3.519*** (0.513)	-2.801*** (0.701)
Company-Government	0.0432 (1.217)	1.826 (2.092)	0.550 (0.523)	0.960 (0.834)
University-Company-Government	16.952*** (2.071)	35.071*** (3.630)	-0.202 (0.889)	-0.803 (1.448)
Multiple "Other"	0.348 (0.767)	4.318*** (1.380)	-2.627*** (0.330)	-2.745*** (0.551)
Number of IPC Codes	0.408*** (0.021)	0.408*** (0.030)	0.898*** (0.009)	1.014*** (0.012)
IPC Section Symbol A	-0.044 (0.259)	-0.392 (0.366)	0.982*** (0.111)	-0.566*** (0.146)
IPC Section Symbol B	5.946*** (0.510)	7.794*** (0.721)	-1.422*** (0.219)	-0.519* (0.287)
IPC Section Symbol D	-0.655 (1.705)	0.919 (2.566)	3.247*** (0.732)	7.714*** (1.024)
IPC Section Symbol E	-1.855 (3.893)	-5.858 (5.358)	38.604*** (1.672)	53.932*** (2.137)
IPC Section Symbol F	5.082*** (1.746)	4.913** (2.329)	-4.398*** (0.750)	-5.337*** (0.929)
IPC Section Symbol G	1.543*** (0.276)	2.054*** (0.392)	-0.274** (0.118)	-0.290* (0.156)
IPC Section Symbol H	6.446*** (1.062)	8.613*** (1.485)	1.092** (0.456)	2.965*** (0.592)
Constant	42.842*** (0.634)	50.869*** (0.879)	3.348*** (0.272)	2.102*** (0.351)
Observations	137,947	88,585	137,947	88,585

R-squared	0.103	0.112	0.128	0.136

Standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*
Note that the following variables were controlled for in these regressions (not shown in the table for brevity): dummy variables for Assignee Country and Publication Year.

5 CONCLUSIONS

5.1 SUMMARY OF FINDINGS

In this study, I investigate the effects of cross-organizational collaborations, particularly those involving companies and universities, on the quality of innovations in biotechnology. Overall, my empirical results show that patents with multiple assignees—evidence of collaboration between at least two organizations—tend to have greater patent value, proxied by number of forward citations and patent family size, than patents with only a single assignee. Upon examination of the specific collaborators contributing to the multiple-assignee relationships, I find that patents produced by multiple companies, university-company, and university-company-government collaborations receive a higher number of forward citations relative to patents produced by a single company assignee. This positive effect is relatively small for patents with multiple companies and university-company collaborators as the assignees; the number of forward citations is found to be, on average, about 5 citations more for patents with multiple companies as the assignees rather than a single company assignee for our full sample and restricted sample of U.S.-based patents only, respectively, and about 2-3 citations more for patents with university-company assignees rather than a single company assignee. However, by far the strongest statistically significant effect is observed when a university-company-government collaboration is involved; these relationships correlate to patents with about 17 citations more than a single company assignee on average, and the difference is as large as 35 citations for U.S.-based patents. These observations highlight the importance of the relationships

between universities, companies, and government—the three main players in the Triple Helix—in maximizing innovation quality in the biotechnology space. In addition, it should be noted that the results for the U.S.-only population are similar to those for the 16-country sample, indicating that the results of this study are applicable for both patents owned by assignees within the U.S. and by assignees from the other major patenting countries outside of the U.S.

When examining simple patent family size as the proxy for patent value, I find that company-company collaboration correlates with increased patent value relative to patents with a single company assignee, but do not demonstrate a benefit from any other form of collaboration. This effect may be attributed to simple patent family size being perhaps a better proxy for the *commercial* value of the invention, as it reflects a company's business interests in seeking IP protection in foreign countries; organizations may only choose to patent in countries where they see market potential. In this way, the simple patent family size is dictated by the assignee organization itself, in contrast to the number of forward citations, which is not controllable by the assignee organization. Similarly, while cross-organizational collaboration may add innovation value that may be beneficial externally, it does not necessarily add commercial value to the assignee organization itself. Another possible explanation is suggested by Guellec & van Pottelsberghe de la Potterie (2000): patent family size may be correlated with patent value only up to a certain threshold, as patent protection in a small number of larger countries may be sufficient. Thus, the observation that simple patent family size is, on average, about 4 patents more for patents with multiple companies as the assignees rather than a single company assignee suggests that companies may still be the major drivers of the commercialization of innovations, while the role of governments or universities may be less important in this sphere. Additionally,

it is possible that inventions developed by government agencies and universities have high scientific value but not necessarily high business value.

On the whole, the results support the research hypothesis that cross-organizational collaborations—particularly company-company, university-company, and university-company-government collaborations—can generate higher quality innovations in the biotechnology field, but reveal that this effect is sensitive to the measure of innovation quality used.

5.2 IMPLICATIONS OF FINDINGS

Because taxpayer money from the American public is being used not only to fund the agencies responsible for activities such as granting and enforcing patents, regulating drug approvals, and providing federal R&D funding, it logically follows that the federal government should recognize and seek to understand its essential role in the Triple Helix of innovation. Characterizing the existing relationships between the three players in the Triple Helix is the first step in optimizing their interactions for maximum research efficiency, productivity, and success of innovation.

Only a small percentage (about 6%) of the patents in the 16-country dataset had government listed as an assignee. While many of the assignee organization types involving government were not found to correlate to higher patent quality than a single company assignee, the assignee type embodying the Triple Helix model—the university-government-company assignee type—was shown to correlate with higher patent quality as proxied by number of forward citations. While, on the one hand, this evidence could serve as motivation for the government to increase the frequency of its involvement in university-government-company collaborations, it is worth noting that the Triple Helix model may also be fulfilled by other means aside from direct government involvement in patenting, which is measured in the

regression model employed in this research. That is, other government contributions play a role in the success and high innovation quality of patents with non-government assignee types.

For instance, while the company-company collaborations correlating to increased patent family size and are mostly outside of the jurisdiction of the federal government, as these are handled largely within the private industry, the government should nonetheless be aware of the important role that patent policy plays in mediating these types of collaborative relationships within the private sector. Similarly, the federal role in mediating technology transfer between universities and companies is responsible for many of the university-company collaborations represented in this dataset. The government also has a hand in promoting research in the field of biotechnology in general through providing grants and subsidies to both companies and academic institutions. All of these factors should be considered in understanding the complex role played by the government alongside universities and companies in the Triple Helix of innovation. This work may prove informative in guiding the federal government's decisions regarding not only direct patenting, but also other activities such as optimization of R&D funding patterns and potential incentivization of industry-academia collaborations through funding and patent policy to promote successful innovation in the field of biotechnology.

5.3 Limitations and Future Work

A limitation of this study is that patents are not a perfect measure of innovation; many valuable inventions are never made public or patented, but rather are kept as trade secrets. In this case, my dataset would exclude these innovations. Another limitation is that, in this analysis, I do not control for individual organizations' capacity for innovation. Even within the same assignee organization type—for instance, companies—there is significant heterogeneity in the organization's ability to conduct R&D. For example, a large company may have significantly

greater resources and financial ability to conduct R&D than a small company. Also, the type of innovation developed through multi-organizational collaboration may differ significantly in nature from the type of innovation developed by companies alone. The metrics used in this study—number of forward citations and simple patent family size—may not accurately capture this difference.

Additionally, while the list of IPC codes used to capture patents falling in the biotechnology sector most likely captured the majority of the relevant patents, there is the risk that new IPC subsections pertaining to biotechnology patents have been developed since the list of codes was released, resulting in the utilized list perhaps not capturing all relevant patents. For this reason, a new and updated list of IPC codes pertaining to biotechnology patents could be developed for future work that aligns with a more recent edition of the IPC system.

The results are consistent with the idea that cross-organizational collaboration can be useful for producing high-quality innovations. Research has shown that assembling teams from "diverse" backgrounds—including not only gender, age, and nation of origin but also career path and industry background—is positively correlated to innovation. For example, in a study examining a company's level of innovation examined as a percentage of total revenue from new products and services launched over the past three years, Lorenzo et al. (2018) found that companies reporting above-average diversity on their management teams also reported greater innovation revenue (45% of total revenue as opposed to just 26% for companies reporting below-average leadership diversity). If one considers gaining project contribution from various organizations as attaining a diverse set of perspectives on a project, the results of this research may suggest, similarly, that diversifying a project team may also improve innovation.

However, proof of causality is not possible due to the regression approach to analysis of the dataset. That is, it is challenging to discern whether high patent quality *results from* cross-organizational collaboration, or whether, on the other hand, high-importance projects demand or attract multiple contributors. It is possible that the correlation between patent quality and cross-organizational collaboration is related to the idea that larger-scale, more impactful projects tend to attract more experts and therefore often call for cross-organizational collaboration. Using this argument, a small-scale, simpler project may be accomplished easily "in-house" without seeking collaborators from other organizations. Future work might benefit from investigating the scale or ambitiousness of some of the projects resulting in patents with multiple assignees to seek clarity on the nature of this correlative relationship between patent quality and multiple patent assignees. Another possible hypothesis explaining the correlation between patent quality and multiple patent assignees—as seen when using number of forward citations as the measure of patent quality—is that having multiple organizations involved in the patent simply increases *exposure*, rather than *quality.* This might be further analyzed by examining what proportion of the forward citations are actually self-citations by one of the contributors on the original patent.

An additional consideration is that cross-organizational collaboration may be driven by a variety of factors. In this study, I do not explicitly address the endogeneity of organizations' collaboration decisions, which may pose a threat to the internal validity of my results. Thus, my research findings only provide suggestive evidence that collaboration may improve the quality of innovation. The field might benefit from some descriptive research—perhaps involving interviews with decision-makers within patent contributors' organizations—to ascertain the motivation behind decisions to engage in external collaborations. Additionally, alternative data types—including academic publications, commercial financial figures, or, in the case of

biotechnology, FDA drug approvals—beyond simply patent data as a metric for innovation quality could be applied to diversify the body of research and provide additional insights into the relationship between cross-organizational collaboration and quality of innovations.

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ACKNOWLEDGEMENTS

Ben Grande, Mathematical Modeling PhD Student at RIT: data science assistance.

APPENDIX 1: IPC CODES USED FOR PATENT SEARCH

Table A1a: Biotechnology-related IPC codes used to obtain dataset, with description of technologies covered by these classifications (WIPO, 2022).

IPC	**Description**
A01H1/00	Processes for modifying genotypes
A01H4/00	Plant reproduction by tissue culture techniques
A61K38/00	Medicinal preparations containing peptides
A61K39/00	Medicinal preparations containing antigens or antibodies
A61K48/00	Medicinal preparations containing genetic material which is inserted into cells of the living body to treat genetic diseases; Gene therapy
C02F3/34	Biological treatment of water, waste water, or sewage; characterised by the microorganisms used
C07G11/00	Antibiotics
C07G13/00	Vitamins of unknown constitution
C07G15/00	Hormones
C07K4/00	Peptides having up to 20 amino acids in an undefined or only partially defined sequence; Derivatives thereof
C07K14/00	Peptides having more than 20 amino acids; Gastrins; Somatostatins; Melanotropins; Derivatives thereof
C07K16/00	Immunoglobulins, e.g. monoclonal or polyclonal antibodies
C07K17/00	Carrier-bound or immobilised peptides; Preparation thereof
C07K19/00	Hybrid peptides (hybrid immunoglobulins composed solely of immunoglobulins)
C12M	Apparatus for enzymology or microbiology
C12N	Microorganisms or enzymes; Compositions thereof; Propagating, preserving, or maintaining microorganisms; Mutation or genetic engineering; Culture media
C12P	Fermentation or enzyme-using processes to synthesize a desired chemical compound or composition or to separate optical isomers from a racemic mixture
C12Q	Measures or testing processes involving enzymes, nucleic acids or microorganisms; Compositions or test papers therefor; Processes of

	preparing such compositions; Condition-responsive control in microbiological or enzymological processes
C12S	Processes using enzymes or micro-organisms to liberate, separate or purify a pre-existing compound or composition; Processes using enzymes or micro-organisms to treat textiles or to clean solid surfaces of materials
G01N27/327	Biochemical electrodes
G01N33/53*	Immunoassay; Biospecific binding assay; Materials therefor (medicinal preparations containing antigens or antibodies)
G01N33/54*	Double or second antibody …with steric inhibition or signal modification, e.g. fluorescent quenching; …with an insoluble carrier for immobilising immunochemicals; …the carrier being organic; Synthetic resin …as water suspendable particles; …with antigen or antibody attached to the carrier via a bridging agent; Carbohydrates, e.g. dextran …with antigen or antibody entrapped within the carrier
G01N33/55*	Carbohydrates, e.g. dextra …the carrier being inorganic; …Glass or silica; …Metal or metal coated; the carrier being a biological cell or cell fragment, e.g. bacteria, yeast cells; …Red blood cell; Fixed or stabilised red blood cell; …using kinetic measurement, i.e. time rate of progress of an antigen-antibody interaction; …using diffusion or migration of antigen or antibody; …through a gel, e.g. Ouchterlony technique
G01N33/57*	Immunoelectrophoresis for venereal disease, e.g. syphilis, gonorrhea, herpes; …for enzymes or isoenzymes; …for cancer; …for hepatitis; …involving monoclonal antibodies; …involving limulus lysate
G01N33/68	Immunoelectrophoresis involving proteins, peptides or amino acids
G01N33/74	Immunoelectrophoresis involving hormones
G01N33/76	Immunoelectrophoresis involving Human chorionic gonadotropin
G01N33/78	Immunoelectrophoresis involving Thyroid gland hormones
G01N33/88	Immunoelectrophoresis involving prostaglandins
G01N33/92	Immunoelectrophoresis involving lipids, e.g. cholesterol

Table A1b: Definitions of IPC section symbols (WIPO, 2022).

IPC	**Description**
A	HUMAN NECESSITIES
B	PERFORMING OPERATIONS; TRANSPORTING
C	CHEMISTRY; METALLURGY
D	TEXTILES; PAPER
E	FIXED CONSTRUCTIONS
F	MECHANICAL ENGINEERING; LIGHTING; HEATING; WEAPONS; BLASTING
G	PHYSICS
H	ELECTRICITY

APPENDIX 2: SUMMARY STATISTICS FOR VARIABLES IN DATASET

Table A2: Number of Patents in the Dataset Published Each Year from 2000 to 2019 in the full 16-country Sample

Publication Year	Frequency	Percent (%)
2000	5,126	4
2001	5,786	4
2002	5,353	4
2003	5,078	4
2004	4,413	3
2005	3,889	3
2006	5,743	4
2007	5,490	4
2008	5,258	4
2009	5,541	4
2010	6,983	5
2011	6,945	5
2012	7,118	5
2013	7,576	5
2014	8,824	6
2015	9,416	7
2016	9,417	7
2017	9,984	7
2018	9,775	7
2019	10,232	7
Total	137,947	100

Table A3: Frequency of Assignee Country in in the full 16-country Sample

Country		**Frequency**	**Percent (%)**
1	United States	88,585	64
2	Japan	11,031	8
3	Germany	6,750	5
4	Great Britain	4,269	3
5	France	3,901	3
6	Switzerland	3,667	3
7	Canada	3,396	2
8	Korea	2,985	2
9	The Netherlands	2,638	2
10	Denmark	2,041	1
11	Israel	1,715	1
12	China	1,490	1
13	Australia	1,463	1
14	Taiwan	1,454	1
15	Belgium	1,325	1
16	Sweden	1,237	1
Total		137947	100

Table A4: Frequency of Assignee Organization Types for Patents with First Listed Assignee from the United States, Japan, Germany, Great Britain, France, Switzerland, Canada, Korea, the Netherlands, Denmark, Israel, China, Australia, Taiwan, Belgium, or Sweden

Assignee Organization Type	Frequency	Percent (%)
Single Company	61,344	44
Single Government	4,972	4
Single University	26,172	19
Single "Other"	1,150	1
Multiple Companies	25,957	19
Multiple Universities	4,242	3
Multiple Governments	475	0
University-Company	7,381	5
University-Government	1,305	1
Company-Government	1,256	1
University-Government-Company	428	0
Multiple "Other"	3,265	2
Total	137,947	100

Table A5: Frequency of Assignee Organization Types for Patents with First Listed Assignee from the United States Only

Assignee Organization Type	Frequency	Percent (%)
Single Company	37,966	43
Single Government	3,597	4
Single University	19,954	23
Single "Other"	457	1
Multiple Companies	16,360	18
Multiple Universities	3,349	4
Multiple Governments	366	0
University-Company	3,777	4
University-Government	771	1
Company-Government	541	1
University-Government-Company	178	0
Multiple "Other"	1,269	1
Total	88,585	100

Table A6: Summary Statistics for the Number of IPC Codes Associated with each Patent in the full 16-country Sample

	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
Number of IPC Codes	137,947	7	6	1	169

Table A7: Number of Patents Associated with each IPC Section Symbol in the full 16-country Sample

IPC Section Symbol	Frequency	Percent (%)
A	65,874	48
B	8,204	6
C	111,465	81
D	635	0
E	121	0
F	617	0
G	36,628	27
H	1,694	1