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Essays on Innovation, Strategy and Competition

A dissertation presented

by

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Essays on Innovation, Strategy and Competition

Abstract

This dissertation is composed of three essays on innovation, strategy and competition. The first essay studies how entry of patent intermediaries known as "patent assertion entities" (PAEs) impacts behavior of other firms in the patent space. It uses deaths of individual patent owners to exogenously identify PAE patent acquisitions, and estimates its impact on follow-on citations. Finally, it shows that after being acquired by PAEs, patents lose a large portion of their follow-on citations. These effects are driven almost entirely by citing behavior of large entities and are robust to controlling for patent examiner-added citations. This effect disappears once the acquired patents expire, indicating that large entities may be acting strategically to reduce the likelihood of patent assertion. The second essay investigates patent disclosure processes at seven large Standard-Setting Organizations (SSOs) where participating entities have a choice between specific patent disclosures and broad generic disclosures. It finds that large, downstream firms who face large technology search costs prefer to use generic patent disclosures. In addition, it shows that higher quality patents are more likely to be disclosed in specific disclosures, because they are more likely to be monetized through licensing. The third essay estimates the causal impact of research expenditures on scientific output. Unexpected college football outcomes provide exogenous variation to university funds, and in turn, research expenditures in the subsequent year. Using this variation, this essay estimates the dollar elasticity of scholarly articles, new patent applications, and the citations that accrue to each.

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Dedicated to my family.

Introduction

How do firms adjust their strategies in response to environmental pressures and competition? And, more importantly, how do those dynamic processes impact technological innovation? These are some of the key questions in strategy and economics, and those that have generated a significant amount of attention over the years. Situated at the intersection of law, economics, and firm strategy, this dissertation sheds more light on these topics as it focuses on specific processes that can catalyze or inhibit innovation. In particular, three such phenomena are examined in detail: 1) entry of patent intermediaries, 2) competition in standard-setting processes, and 3) productivity of knowledge-generating institutions.

The first essay shows that highly litigious activity of "patent trolls" significantly reduces subsequent citations of affected technologies, potentially balkanizing the technological space and reducing follow-on innovation.

Markets for technology are plagued with frictions – high search costs and uncertainty being the main culprits. An intense policy debate is brewing about the role of market intermediaries in markets for technology and their effects on market efficiency and innovation. While some specialized intermediaries attempt to foment efficient exchanges of patent rights, others attempt to capitalize by enforcing patents on a large scale. A drastic rise in activity of patent assertion entities, commonly referred to as "PAEs" or "patent trolls" is behind the three-fold increase in the number of US patent assertion cases in the last five years. Rather than develop new technology themselves, patent trolls specialize in opaquely acquiring existing patents and strategically asserting them in a very aggressive fashion. Because of their litigation-optimized organizational form and stealthy operations, patent trolls are particularly interesting as they represent an asymmetric threat for operating firms. Despite the fact that a prospect of patent litigation can have a significant impact on firms' behavior, interrupting knowledge flows and diverting them around technological areas where patent trolls are present, there is a lack of empirical work on this issue.

This essay uses deaths of individual patent owners as an instrument for patent troll activity, since estates tend to sell or license out intellectual property assets quickly. It shows that a highly disproportionate number of recently deceased inventors' patents is acquired by patent trolls, and finds that after patent troll acquisitions, large firms strongly avoid citing these patents. This effect disappears after the focal patent expires. Moreover, I show that the instrument is a good predictor of patent troll presence in a patent class, and find that firms avoid these patent classes while the troll-owned patents are legally valid. After being acquired by patents trolls, patents lose almost 6 citations, or almost 40% of all citations on average. These effects are driven almost entirely by the citing behavior of large entities and are robust to controlling for patent examiner-added citations. My results raise two important issues: the first one is that aggressive patent assertion could potentially have negative effects on knowledge flows, and the second one is that firms may respond to litigation threats in patent space by strategically avoiding sourcing of technological knowledge from threatened domains, thus raising doubts about "inequitable conduct" policy and its effectiveness in preventing strategic citations of prior art. Both of these have a potential to significantly impact the performance of the innovation ecosystem and stand out as important areas to be studied in the future.

The second essay, co-authored with Josh Lerner and Jean Tirole, explores the process of selection of standard essential patents, their subsequent inclusion in patent pools, and firm-dependent patent disclosure strategies.

Technological standards determine functionalities, capabilities, interoperability and evolution of products, services and technologies. A high degree of interdependence and complexity in modern high-tech product architectures makes technological standards ubiquitous and more important than ever. Standards are usually shaped by standard-setting organizations (SSOs) and participating firms required to disclose all standard-essential patents in their ownership. An important policy issue in standard setting is that patents that are ex-ante not important may, by being included into the standard, become standard-essential patents. In an attempt to curb the monopoly power that they create, most standard settings organizations require the owners of patents covered by the standard to make a loose commitment to grant licenses on fair, reasonable and nondiscriminatory terms, even though such commitments are often conducive to intense and costly litigation activity ex-post. Commitments made during the standardization process are at the heart of many legal battles, as some firms have made attempts to "game" the system. SSO-participating entities usually have a choice between specific patent disclosures and broad generic disclosures. Little is known about what drives their disclosure strategies and how they may be impacted by the underlining patent quality.

In this study, a novel dataset is created by linking 21 patent pools with relevant technology standards at seven large SSOs and combining standard-disclosed and pooled patent data with firm financial information. Subsequent analysis finds that, consistent with theory, large firms with downstream presence face large technology search costs and are more likely to utilize generic patent disclosures. In addition, it also finds that higher quality patents are more likely to be disclosed in specific disclosures, because they are more likely to be monetized through licensing. These results indicate that firms approach standardization process strategically and closely align patent disclosure decisions with their competitive advantage.

The third essay, co-authored with Thomas Wollmann, is the first study that derives a causal estimate of university research funding on scientific output, where that output is measured in citation-weighted academic publications and citation-weighted patent applications.

Colleges and universities conduct a gargantuan share of research and development in the United States, and account for the majority of basic science expenditures. Without any downstream presence of their own, these institutions act as highly specialized "knowledge generators" in the national innovation economy and help drive economic growth through scientific discovery. Unfortunately, the high cost of research often makes funding a limiting factor for scientific advance and represents a policy matter of national importance. At this point, little is known about the causal impact of money on science, despite its importance for determining the socially-optimal level of R&D.

This study seeks to inform the debate about the funding of scientific research in the United States and provide insight into how specialized knowledge producers respond to unexpected positive shocks in R&D funding. It estimates the dollar elasticity of research output at American universities by using unexpected NCAA football outcomes to exogenously shift research budgets across schools and time. After presenting a novel dataset of historic team success, measured by vote tallies from the Associated Press Top 25 Poll, this essay shows that unexpected within-season changes to this measure are strong predictors of university-sponsored research funding in the subsequent period. These changes do not predict university-sponsored funding in the contemporaneous period or federally-sponsored research in any period, lending further support for the instrument. An elasticity of 1.91 is found when the outcome is patent applications count and 3.3 when the outcome is patent citations count; 0.31 when the outcome is scientific publications count, and 0.59 when the outcome is count of citations that subsequently accrue to those publications. The cost to the university, at the margin, of additional research funding to generate an idea worth of filing a patent application is estimated to be between $2.6 and $3 million. For each outcome, the instrumental variable results contrast sharply with the OLS estimates, which are significant but near zero and would lead policymakers to underinvest in research. These results imply that there are constant positive returns to funding of university R&D, and that optimal policy decision should not seek to reduce funding to R&D.

Chapter 1

Firms and Patent Assertion Entities

1.1 Introduction

While spurts in patent enforcement activity have not been an uncommon sight in the past, over the last five years, patent assertion entities "trolling" the patent space have been a major contributor to the precipitious rise in the number of patent assertion lawsuits. Without manufacturing or innovative footprint of their own, these opaque and highly specialized entities acquire and assert patents *en masse*. In 2012 alone, the total number of patent lawsuits rose by 29% over the previous year and almost doubled since 2009 [PricewaterhouseCoopers, 2014]. A portion of new lawsuits were certainly caused by competitive battles of large firms, especially those in the smartphone arena. However, over 60% of all new lawsuits filed in 2013 originated from PAEs, while the top 10 plaintiffs filing most new cases in 2013 were all PAEs [Byrd and Howard, 2014, RPX Corporation, 2014]. As the PAE activity intensified, so did the discourse between the supporters on the one side, and the opponents of patent assertion business model on the other side.

The main point of contention focuses on the role of PAEs in the technological ecosystem and whether their net impact on cummulative innovation is positive or negative. Empirical work on PAEs is scarce for at least two reasons. First, the steep rise in PAE activity is relatively recent, and data identifying patent portfolios held by PAEs is lacking. Second, PAEs select which patents to acquire and assert, so the relationship between PAE activity and subsequent firm behavior will be biased away from—or even the wrong sign as—the true causal impact of PAEs.

In this paper, I construct a new dataset of PAE patent acquisitions and use the death of individual patent owners as an instrument for PAE patent acquisition activity. When a patent owner dies, estate trustees tend to sell or license intellectual property assets, which can be acquired by PAEs. I show that a disproportionate number of these patents ends us being either acquired or licensed by PAEs, and later used to extract rents from other firms in the technological space. I show that, subsequent to patents being acquired by PAEs, large entities strongly avoid citing them to reduce the risk of becoming an assertion target. This effect disappears after the patent expires. On the other hand, small entities cite PAE-owned patents more, with this effect increasing in magnitude after the patent expires. This is consistent with previous studies indicating that large firms are more aware of their environment and highly strategic in their choices of which patents to cite, and which technology to build-on [Allison and Lemley, 1998, Ziedonis, 2004, Lampe, 2012]. My results also indicate that PAE activity could, in fact, boost cumulative innovation amongst small companies, to the extent that those are proxied by the patent citation patterns.

A subject of an intense debate, the impact of recent spike in PAE activity on firms and innovation is important for inventors, managers, lawyers, academics, investors, and policymakers alike[1]. On one side of the aisle, arguments for innovation-enhancing role of PAEs underline their importance in reducing technology search costs, increasing liquidity of market for patents and providing previously scarce patent monetization and enforcement opportunities for small firms and individual inventors [McDonough, 2006, Geradin et al., 2011, Risch, 2012]. On the other side, opponents of PAEs underline deadweight loss arising from unnecessary licensing fees, high litigation costs and skewed incentives to innovate

[1]See the Federal Trade Commission and the Department of Justice "patent monetization entity Activities Workshop":
http://www.ftc.gov/news-events/events-calendar/2012/12/patent-assertion-entity-activities-workshop (last accessed on 10/10/2014)

[Bessen et al., 2011]. This controversy has even attracted the attention of the White House to make a call for a deeper patent reform and invited remarks by the US President Barack Obama[2]:

> The folks [PAEs] that you're talking about are a classic example. They don't actually produce anything themselves. They're just trying to essentially leverage and hijack somebody else's idea and see if they can extort some money out of them.

So far, 17 bills dealing with various aspects of patent reform have been introduced by the US Congress over the last two years to deal with the glut of PAE-intiatied patent assertion lawsuits.[3] It is important to note that while patent enforcement in itself is one of the key components of a robust intellectual property system, the concern over extensive PAE patent enforcement arises mainly from the large-scale economic impact and all-too-common lack of transparency in PAE operations. Assertion of patent rights is a mechanism designed to protect temporary exclusivity of patent rights. It is intended to compensate patent holders for their creative endeavors and enhance their incentives to innovate. Not exclusively reserved for firms' competitive maneuvers, patent assertion is also a tool for individual inventors, small and non-profit entites to prevent expropriation and obtain compensation for their innovative efforts. The effects of patent assertion have been studied extensively in law, economics and strategy to show that, as a part of firms' competitive arsenal, it can be used to reduce competitive pressures and increase barriers to entry. For example, established, large firms were found to use assert patents disproportionately against smaller firms, while smaller firms were found to avoid patenting in and entering dense technological areas, especially those with many litigation-happy firms [Lerner, 1995, Lanjouw and Lerner, 2001, Lanjouw and Schankerman, 2001, Cockburn and MacGarvie, 2011]. Firms were also

[2] President Barack Obama, "Fireside Hangout," White House YouTube Channel, February 14, 2013, Accessed May 5, 2015. https://www.whitehouse.gov/blog/2013/02/14/watch-president-obama-answers-your-questions-google-hangout

[3] See Patent Progress website for the full list: http://www.patentprogress.org/patent-progress-legislation-guides/patent-progresss-guide-patent-reform-legislation/ (last accessed on 10/07/2014).

found to be likely to enforce their patent rights to signal "toughness," build reputation in their respective technology and market spaces, and transmit information about the strength of their patent portfolio to potential entrants and competitors [Choi, 1998, Crampes and Langinier, 2002].

While there is empirical evidence that firms react to hold-up threats from *direct competitors* by agressive patent portfolio building, mergers and acquisitions, joint ventures and patent pooling [Hall and Ziedonis, 2001, Ziedonis, 2004], the work on how firms react to PAE activity is scarce. As highly opaque entities without any manufacturing operations of their own, and with patent holdings divided across many shell companies and subsidiaries they are difficult to defeat on a legal battlefield. Extensive patenting gives firms rights to exclude others from utilizing and profiting from patented technologies, while it does not give them absolute rights to practice those patented technologies themselves. This nuanced legal point is what keeps patent assertion business model viable. Conventional intellectual property strategies commonly used to keep competitors at bay are laregly ineffective against PAEs, as they represent an asymmetric threat, and are optimally organized for informational and legal arbitrage in the patent space.

PAE-targeted firms usually have a limited set of options. The first one is to face a long, expensive, and often unpredictable legal battle in order to invalidate PAE-asserted patents or asserted claims of infringement. The prospects of such a battle can be daunting and can make a serious dent in the company value sheet. Hence, a promise of a quick settlement "priced" well below the cost and risk of a protracted patent litigation would look appealing to any rational firm [Cohen et al., 2014, Feldman and Price, 2014]. Many firms favor this less costly option, and in order to avoid protracted litigation, reach a quick settlement with PAEs and pay patent licensing fees to make the threat "go away". This particular PAE strategy flavor has a strange resemblance to organized crime extortion rackets, and has incited some firms to attempt to fight back and counter-sue PAEs under Racketeer Influenced and Corrupt Organizations (RICO) Act, albeit without much success.[4] Firms could also insure themselves

[4]There were two recent, albeit unsuccesful cases where defendants tried counter-suing PAEs under RICO

against patent infringement to cover unexpected litigation costs, but this market is not well developed and the policies are relatively expensive.[5] Firms can also try to pre-empt the threat and reduce the risk of unwelcome assertion by either basing their products on "open" technologies [Lerner and Tirole, 2005] and building the chest of prior-art publications [Baker and Mezzetti, 2005], or signaling that their activities are not related to technological domains rife with PAE activity. In the similar fashion as the biotech firms with high-litigation costs who avoid patenting in technological areas crowded with highly litigious entities [Lerner, 1995], firms can strategically avoid drawing on technology and building on knowledge originating in areas with high PAE activity, if that would decrease their litigation risks.

Most contemporary studies that examine consequences of PAE activity tend to be focused on PAE business models, their direct costs to the firms and immediate outputs like R&D spending and patent counts, while overlooking these important strategic choices. Merges [2009] suggests that extensive patent trolling could result in an overall reduction in innovation and the number of new products to hit the market and Chien [2014] provides descriptive evidence that small firms targeted by PAEs are often disrupted, forced to make operational as well as strategic trade-offs and sometimes even exit product markets. Relatedly, Bessen and Meurer [2014] estimate the aggregate cost of PAE litigious activity to be a whopping $29 billion, and suggest that monetary transfer to inventors represents a very small portion of that amount — sometimes as low as 5% of the direct cost to PAE-targetted firms. However, while suggesting that the high cost of PAE litigation may force firms to reallocate funds from R&D to legal activities and reduce innovation, they do not provide any direct evidence as to what the impact may be on *how* firms may respond to reduce PAE exposure and *how* these responses may play out in the patent space. Several recent studies

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Act. The first one was jointly brought by Cisco, Netgear and Motorola against Innovatio IP, while the second one was filed by FindTheBest against Lumen View. Also, in 2011, Kaspersky Labs sent a letter to FBI requesting that they investigate RPX Corp for RICO violations because of suspicious, extortion-like behavior related to a pending patent lawsuit brought on by IPAT, LLC – a firm who had previously licensed asserted patents to RPX.

[5]General patent litigation insurance premiums range between 1-5% of the insured amount, which can reach hundreds of millions. (website http://www.hahnlaw.com/references/501.pdf (accessed 10/27/2014)) As a defensive patent aggregator, RPX Corporation does offer a specific PAE insurance policy with premiums of about $7,500 for $1 million in coverage. (http://www.rpxcorp.com/rpx-services/rpx-litigation-insurance/)

try to address this issue in more detail: Cohen et al. [2014] and Smeets [2014] find that patent litigation negatively affects corporate R&D spending and output for publically listed US firms, particularly if initated by a “patent troll”, while Tucker (2014a; 2014b) specifically addresses trolling effects and finds that PAE activity may reduce venture capital investment, as well as incremental product innovation and downstream sales. In high-tech industries that rely on standardization to ensure device interoperability, the risks and potential costs stemming from PAE-related hold-up can be exceptionally high[6] [Shapiro, 2001].

I follow this line of research and examine the effects of increased PAE exposure on firm behavior and cumulative innovation by focusing not on monetary measures of R&D spending or direct patent counts, but rather on *how* firms try to reduce litigation risks following the entry of PAEs. This paper contributes to a long line of literature on patent rights, patent assertion, strategy and innovation, and is close in spirit to Lerner [1995], Lampe [2012] and Galasso and Schankerman [2015]. While Galasso and Schankerman [2015] show that a growth in cumulative innovation as proxied by patent citations after invalidations of patents owned by large firms stems from increased participation of small firms, I show that the negative effect on patent citations after PAE entry is due to strategic behavior of large firms, i.e. PAE acquisition of a patent causes large firms to cite that patent less. The effect on small firms is completely opposite. I also contribute to recent set of studies indicating stricter property rights as a damper for follow-on innovation [Murray and Stern, 2007, Williams, 2013] and show that a rampant over-enforcement of property rights forces the firms to respond in a way that could potentially dampen cumulative innovation, especially for those firms more aware of litigation risks.

The rest of this paper is organized as follows. Section 2 examines the patent assertion entities in more detail and provides theoretical implications of their activity. Section 3 discusses knowledge flows and their relationship with patent citations, innovation and

[6] A good example is the case of of Wi-Fi technology and Innovatio IP Ventures. Wi-Fi technology is based on a IEEE 802.11 standard, and after Innovatio IP Ventures acquired a set of patents declared essential to this standard, they proceeded to send patent infringement letters to thousands of Wi-Fi end-users: hotels, coffee shops, restaurants, grocery stores and many more.

firm strategy. Section 4 describes the data sources. Section 5 presents variables, and lays out empirical strategy. Section 6 gives the descriptive statistics and model robustness tests. Section 7 provides additional discussion of the results and shortcomings of the study. Section 8 concludes.

1.2 Patent Monetization Entities

1.2.1 Overview

Although often hailed as a recent phenomenon, the business of purchasing and asserting patents without clear intention to commercialize them has been around since the early days of US patent system.[7] Patent trade was surprisingly well developed during 19th century and many specialized intermediaries were participating in the market, including patent assertion entities [Lamoreaux and Sokoloff, 1999, Khan, 2014]. There are numerous examples of various non-manufacturing entities engaging in patent assertion practice during industrial revolution and targeting many different industries: smelting, agriculture, woodworking, railroads and even automobiles[8]. Today, PAEs fall in the class of modern intellectual property intermediaries together with IP brokers, defensive patent aggregators and hybrid IP intermediaries [Hagiu and Yoffie, 2013]. They do not manufacture any products and capitalize on information asymmetry in the market by acquiring patents from other entities only to later assert them against other, usually producing firms. Because of the secrecy surrounding PAE operations, it is not always immediately clear where acquired patents originated: some are acquired from large, active operating companies,[9] while the significant portion is acquired from small firms and individual inventors. For example, Risch [2015] puts the number of PAE patents acquired from individuals and their companies to over 43%, and Chien [2012] reports that patents acquired from individuals compose almost 30% and

[7]"Trolling" as a business model is not exclusive to patents only. This phenomenon also impacts other intellectual property assets classes, like copyrights and trademarks. See Folgers [2007] or Sag [2015], for example.

[8]See Merges [2009] and Khan [2014] for examples.

[9]This phenomenon is known as "patent privateering" [Ewing 2012a, 2012b].

those acquired from small companies—including individual-inventor-owned companies—almost 50% of the overall PAE patent acquisitions made in 2010-2011.

These patent acquisitions are often done when original owners are under distress and have a urgent need to monetize their assets in a "fire sale": costly divorce proceedings facing individual inventors[10] or financial problems facing a firm, individual inventor or a start-up are common reasons for patents to be sold[11]. PAE arbitrage strategy is further corroborated by PatentFreedom[12], a firm that collects and analyzes data related to PAE activity. According to PatentFreedom, only 19% PAEs are original patent assignees, while 69% are pure patent acquirers.[13] Their data also indicates that almost two-thirds of patents litigated by PAEs in 2011-2012 were patents acquired from someone else.

In these transactions, PAEs effectively utilize frictions in the market for patents: asymmetric information and the lack of an efficient price discovery mechanism allow them to "buy low and sell high". Patents are usually acquired for a fraction of the revenues generated via subsequent licensing and assertion. This type of market arbitrage is largely similar to strategies employed by art dealers and brokers.[14] In the case of PAEs, information arbitrage is combined with legal arbitrage to enable them to deliver a maximum punch. For a manufacturing firm, the strategy of "mutually assured destruction" is a credible detterent and a very effective response to patent assertion by another manufacturing competitor. These firms often build large, overlapping patent thickets just so that once a competitor initiates a patent assertion lawsuit, they can respond with an immediate patent assertion lawsuit of their own. For example, when Apple sued Samsung for infringement of its patented designs in the US, Samsung immediately countersued Apple for infringement of its 3G technology patents. As Hall and Ziedonis [2001] and Ziedonis [2004] point in

[10]Comment made during in-class discussion by an executive from Intellectual Ventures.

[11]See McFeely [2008] for an example.

[12]As of June 2014, PatentFreedom is a part of RPX Corporation, a large defensive patent agregator.

[13]12 % are a blend of the two. For additional information, see https://www.patentfreedom.com/about-PAEs/background/

[14]See Wall Street Journal "Why You Can't Always Trust Art Dealers " for more detail.

their study of patenting in semiconductor industry, this strategy usually results in a mutual hold-up stalemate and resolves in a settlement involving cross-licensing of each other's patents. Kab-tae Han, a senior intellectual property manager of Samsung's digital media business reveals this approach as a key part of their IP strategy [Han, Kab-tae, 2004]:

> At one time, when we received a patent claim from another company, we did not have any idea how to deal with the situation. It was quite natural that our strategy was focused on how we could pay less. But now we have a relatively good patent portfolio. This means that we can counter-claim against other companies, which leads us to have more cross-licences. We changed our strategy to become more aggressive. We think that having good patents is the best strategy.

When it comes to competitive interactions between large, operating firms and the PAEs, "mutually assured destruction" approach is ineffective since PAEs do not have any downstream presence. So, while Samsung can respond to Apple's patent assertion claims by countersuing Apple and requesting injunction against sales and/or manufacturing of their products, Samsung cannot do that against a PAE simply because there are no products or sales to begin with. For the same reason, cross-licensing is also not a viable strategy against PAEs. In the same interview, Kab-tae Han notes that one of the biggest challenges for companies like Samsung is dealing with upstream patent owners Han, Kab-tae [2004]:

> Another challenge is that many venture companies or individuals who have done only R&D activities come to the manufacturer asking for higher royalties. This is very tough for companies like us.

Recognizing that PAE litigiousness can have adverse effects on firm's incentives to build upon PAE-owned technologies, we can expect a transfer of patent rights to PAEs to lead to a decrease in observable follow-on innovative activity. Jeruss et al. [2012] point out that regardless of whether patent intermediaries assert patents themselves and behave as pure PAEs, or transfer them to other parties to be asserted, the net effect on the market should be the same. However, given that citing and building upon PAE-owned patents might increase the probability of an assertion lawsuit, it is hard to believe that market reaction to PAE-owned patent vs. operating firm-owned patent would be the same. In other words, if a non-practicing entity acquires a patent and transfers it to an operating company for downstream assertion, the market should react in a different fashion than if that patent was to be asserted by the non-practing entity itself. For practicing firms in an industry, building on each-other's technologies and cross-citing each other's patents could help delineate the differences between competing technologies and reduce the probability of a follow-on lawsuit. On the other hand, the effect for PAE-owned patents would be just the opposite.

1.2.2 Impact on Firm Behavior

Firms learn from their experiences. Productivity improvements arising from firms' previous experiences have been documented in various settings: aircraft manufacturing [Alchian, 1963, Mishina, 1999, Benkard, 2000], ship manufacturing [Rapping, 1965, Thornton and Thompson, 2001] and automobiles [Levitt et al., 2013]. This phenomenon of "learning-by-doing" points to the existence of an invisible feedback loop that connects knowledge and capabilities acquired through experience directly to the firm's production function. Firms learn how to source, integrate and utilize knowledge in order to improve their performance [Cohen and Levinthal, 1990]. Experiental learning impacts firm behavior in all aspects of their operations. Since experience comes with age, and firm age is highly correlated with firm size, I expect larger firms to be more strategically astute in the patent space [Jovanovic and MacDonald, 1994, Lerner, 1995, Cabral and Mata, 2003, Ziedonis, 2004]. Large firms patent more, patent more aggressively and have larger patent portfolios [Ziedonis, 2004]. They often have internal patent review boards and employ internal corporate patent counsel [Lerner, 1995]. They carefully manage prior art during patenting process: Alcácer et al. [2009] show that large firms receive larger share of examiner-added citations, and Lampe [2012] shows that they strategically withold prior art to maximize the likelihood of patent issue. Large firms are likely to be more cognizant of an PAE threat, and act to minimize its exposure. Recent public actions of large firms like Google all but confirm their awareness of PAE hold-up risk. For example, in 2014 Google, Cannon, Dropbox and other large companies formed a License-on-Transfer (LOT) coalition that automatically extends a royalty-free patent license to all members when a member-owned patent is sold to a non participating company.[15] This move is largely set to counter a rise in patent privateering and prevent operating companies from contributing to proliferation of PAE activity. Patents can be transferred from operating firms to PAEs and have them act as "privateers" to atack direct competitors with minimal operating firm exposure and without any risk of being counter-sued. Some operating companies could take this strategy one step further and dissagregate their patent holdings across many PAEs to inflict even higher damage on their competitors [16][Lemley and Melamed, 2013].

While there are PAEs who follow the "machine gun" approach and assert their patents widely against as many firms as possible, requesting modest royalties and licensing fees in hope to profit from the sheer scale of the operation,[17] large companies still represent a juicier target. According to PatentFreedom, the top 30 companies most pursued by PAEs account for more than 3300 PAE patent lawsuits between 2009-2014, and are all large, operating companies ranging from Apple and Samsung to Walmart and Target.[18] Many PAEs focus on acquiring higher value patents to position themselves favorably against large, highly profitable companies. This approach has a potential to yield large settlement payoffs, and is further corroborated by Cohen et al. [2014] who find that PAEs opportunistically target firms flush with cash. Proliferation of sofware and business methods patents, and high degree of patent right fragmentation in high-tech industries helped make this a profitable strategy [Lerner, 2010, Feldman and Price, 2014]. A choice of who to pursue in the value chain can have a significant impact on the final payoff: directly asserting patents against an upstream provider in some instances can be more costly and yield a lower payoff than

[15] See http://www.lotnet.com/

[16] For example, if a single technology is covered by a set of N patents, then the patent owner can divide them accross N PAEs, thus fragmenting or "disaggregating" that technology. This patent owner would then maintain a backdoor license to each one of the patents, effectively multiplying the returns from this set of patents by some factor N-k, where N>k>0 . At the same time, any cost for the competitor would be also be multiplied by the same factor.

[17] A case of Wi-Fi technology and Innovatio IP Ventures is a great example.

[18] See https://www.patentfreedom.com/about-npes/pursued/

prosecuting all the downstream users [Feldman and Price, 2014]. In addition, asserting patents against downstream users who may have more elastic demand function and lower switching costs, may put a great deal of indirect pressure on upstream technology providers and force them to license asserted patents, especially in the markets with strong network effects. For example, in his 2013 testimony before the U.S. House of Representatives, Jamie Richardson, a vice president of the White Castle burger chain called for the patent reform and highlighted the waste of company's resources and time caused by frequent PAE patent assertions as well as the subsequent hesitation in the adoption of the new technologies related to online and mobile marketing, ordering and payment systems.[19]

Small firms, on the other hand, have a much more limited arsenal against PAEs at their disposal. In addition to being less knowledgeable about intricacies of the intellectual property space than the large firms, they are also more strapped for cash and more likely to avoid prolonged legal wranglings. Thus a PAE infringement letter is more likely to be settled with a quick license payment and an non-disclosure agreement. Small firms often lack funds to employ in-house patent counsel and may abstain from hiring expensive patent prosecutors. Without added sophistication and experience with patents, these firms are more likely to rely on more visible or in-licensed patents for prior art. In addition, small firms also happen to be less diversified and more likely to have their operations concentrated in a narrow technological domain. Hence, small firms are unlikely to avoid PAE-owned patents as prior art in a strategic fashion.

1.3 Patent Citations and Firm Strategy

Ever since Jaffe et al. [1993] utilized patent citations to study localization of knowledge spillovers, the citations have been widely used in economics and management as a measure of knowledge flows in many different contexts: from academic instutions to firms

[19] *The Impact of Patent Assertion Entities on Innovation and Economy: Hearing Before the House Energy & Commerce Subcommittee on Oversight & Investigation*, United States House of Representatives, 113th Congress (2013) (statement of Jamie Richardson, Vice President of Government, Shareholder and Community Relations at White Castle System Inc.)

[Henderson et al., 1998, Gittelman and Kogut, 2003], within firms [Zhao, 2006, Alcácer and Zhao, 2012], between firms [Rosenkopf and Almeida, 2003, Singh and Agrawal, 2011] and across geographies [Singh, 2005, MacGarvie, 2005]. While patent citations have been used to map out knowledge flows and follow-on innovation, they have also been shown to be susceptible to noise. Alcácer and Gittelman [2006] show that patent examiners add a significant number of patent citations. Roach and Cohen [2013] highlight errors-in-variables problem when patent citations are used as measures of knowledge flows, and identify private knowledge flows and strategic citations as two sources of systematic measurement errors. Other authors have also noted similar issues. For example, firms were found to cite more prior art to strengthen patent claims, enhance patent validity, and reduce the risk of invalidity countersuits [Allison and Lemley, 1998, Harhoff et al., 1999]. Large firms can also cite less prior art to maximize the likelihood of patent issuance [Jaffe et al., 1993, Lampe, 2012]. However, the problem is not only whether firms simply cite more or less, but rather how selective they are in *who* to cite more or less. Whether firms *strategically* cite more or less prior art from their direct competitors, scientific literature or technologically distant small firms can have very different implications. My primary concern is whether PAE acquired patents are going to elicit a heterogenous response with respect to citing behavior by small and large firms, especially considering that large firms have been shown to be strategic in the past.

As a part of patenting process in the United States, inventors are legally obligated to disclose any known prior art, which is captured in the front end of the patent and becomes a part of "citations" or "references" section. Disclosure of prior art carries a lot of weight because it indicates the relationship of the invention to other patented inventions or published works, and is used in determining the exclusionary scope of the patent. Inventors have a "duty of candor" to disclose all relevant prior art and any purposeful omissions can lead to patent being rendered unenforcable due to "inequitable conduct".[20] Since they signal technological relatedness between cited and citing patents, and imply operational

[20]See Code of Federal Regulations: Patents, Trademarks, and Copyrights, 37 CFR §1.56

technological overlap, citations have been noted as a useful link in detecting potential licensing partners [Ziedonis, 2004]. Following the same logic, patent citations can be used as a link to detect potential infringers. One patent attorney's posting on the Intellectual Property Networking group forum on LinkedIn[21], says:

> Forward citations might not be so useful to estimate patent quality but I find them useful to identify possible, if not likely, defendants in patent infringement suits. Yesterday, I took a look at the forward cites for Adaptix, which was purchased by Acacia for $161M. Virtually all of the large forward citing companies were sued by Acacia today!

Ziedonis [2004] shows that, in order to mitigate hold-up risk in technological domains where property rights are fragmented, capital-intensive firms patent and acqire patents more intensively. However, these strategies do not mitigate PAE threats. Since PAEs are optimized to extract rents through patent assertion, any possible connection to a patent in their possession can trigger a legal action. It is not unusual to see more agressive PAEs filing multiple patent assertion lawsuits every week. For example, one of the few publically traded PAEs, Acacia Research, filed as many as 239 patent assertion lawsuits in 2013 [RPX Corporation, 2014]. Given this nature of PAE threat, eliminating any possible connections to patents in their possesion, and attenuating signals of follow-on innovation while the threat is active would behove any firm wary of PAE litigation.

While the firms can reduce PAE litigation risk strategically if they conduct thorough "patent clearance" searches before filing a patent of their own, manufacturing a product, or providing a service, the search costs in technology space are high, making this option very expensive and in some cases even impossible to execute [Mulligan and Lee, 2012]. This is particularly true when it comes to more complex product architectures like integrated circuits or mobile phones, where patent rights covering product components tend to be highly fragmented. There is another, perhaps more sinister reason for firms to avoid

[21] The original post provided the law firm name, the first name and the last initial of the attorney. This attorney was later identified by the author as Janal M. Kalis, a principal at Schwegman, Lundberg and Woessner, P.A. website: http://www.linkedin.com/groups/Do-you-count-forward-citations-1186457.S.89822516 (last accessed 10/28/2014)

clearance searches. If a firm conducts a clearance search and finds that its technology may be infringing on someone else's patents, yet it decides to ignore these findings and rolls the dice that the infringement will go undetected, it exposes itself to claims of willfull infringement. Willfull infringement can be a scary prospect, because it allows the patent owner to request compensatory damages to be enhanced up to three times the amount.

1.4 Data

1.4.1 Description

To identify citation patterns, I use USPTO patent citation data covering the 1982-2012 time period. The USPTO grant data identifies patent references for every published patent and enables us to create backward and forward citation maps. In addition, this data provides additional bibliographic information like the patent classification, application date and the grant date. I use patent application and grant dates combined with patent maintenance fee payment data to determine expected patent term, and examine the effects of PAE activity pre- and post-patent expiration. I calculate patent expiration dates based on USPTO patent term rules for utility patents: for utility patents applied for before June 8, 1995, patent term is set to seventeen years from the grant date, and for utility patents applied for on or after June 8, 1995, patent term is set to twenty years from the application date. In order to keep the patent in force, USPTO requires patent owners to pay patent maintenance fees in three installments: at 3.5, 7.5 and 11.5 years from the date of grant. If any of these installments are not paid, the patent is set to expire early. As Figure 1.1 shows, majority of US patents do expire early.

Some patents also get their terms extended, either because of USPTO-related delays, or because of delays in getting regulatory approvals to release their products to the market. American Inventors Protection Act of 1999 provides for daily patent term adjustment, if the grant delay is caused by USPTO. However, in order for adjustment to be viable, the patent applicant is obligated to continually demonstrate efforts to finalize prosecution. Relatedly,

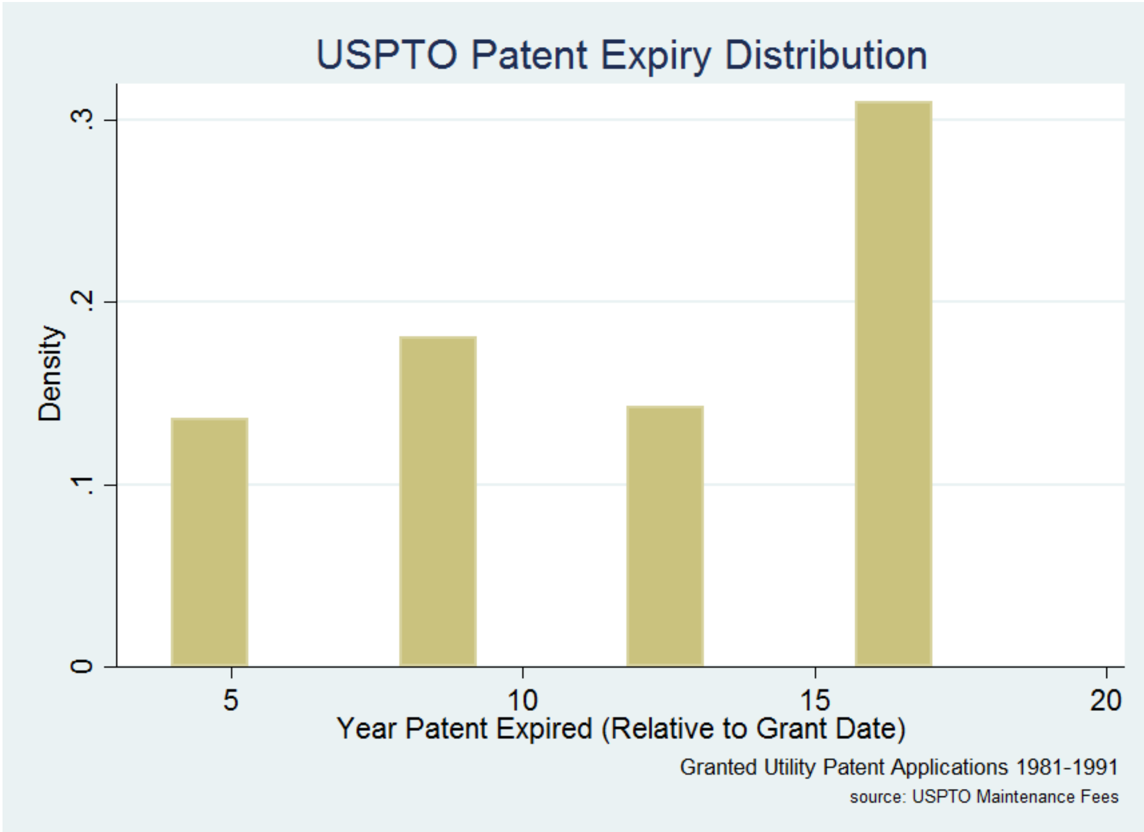

Figure 1.1: *Patent Expiration (1981-2001)*

Hatch-Waxman Act of 1984 allowes patent owners to request patent term extensions equivalent to time "lost" due to pre-market approval requirements before a regulating agency like the Federal Drug Administration (FDA) or The Department Of Agriculture (DOA). I currently do not have the patent term adjustment or the patent term extension data, and do not include them in the patent term calculations. My patent expiry calculations are based on patent application dates and maintenance fee records only. However, while the omission of term extension and term adjustments information may introduce noise into my analysis, it is worth noting that 1) these term changes are going to impact only those patents extended to the full term and 2) existing literature has pointed out that substantial term changes are highly concentrated in pharmaceutical and biotechnology patent classes [Luckow and Balsarotti, 2010]. USPTO also provides a list of patents requesting term extensions under 35 USC §156 (regulatory delay) which contains only 684 patents and almost exclusively impacts pharmaceutical patents .[22]

Starting with 2001, USPTO grant data separately identifies patent references made by the patent applicant from those made by the patent examiner. Examiner-added references represent a significant share of overall patent references, estimated to be as high as 63% for an average patent [Jaffe et al., 2000, Alcácer and Gittelman, 2006] Since examiner-added references can bias my results, I extract examined-added references from USPTO data 2001-2012, and separately classify all references made by patents applied for during that time period into examiner and non-examiner groups.

Deaths of individual patent owners are identified from the patent re-assignment data covering 1982-2012 time period. Patent re-assignment data has previously been used to identify patent trading patterns, but not the singular events affecting patent owners [Serrano, 2010, Galasso et al., 2013]. US patent ownership transfers are recorded in USPTO Patent Assignment Database and uniquely identified by the reel and frame number. Each re-assignment record contains patent and application numbers, and the relevant bibligraphic data: the name of the new patent owner (assignee), the name of the original patent owner (assignor), the date at which the transfer was recorded at the patent office, the date at which the transfer of patent rights was executed, the type and the description of the transaction (conveyance). It is important to note that, while the recordation of the patent ownership transfer is not mandatory in the United States, patent law provides a strong impetus for patent owners to ensure that all patent assignments get properly and promptly recorded. If, for some reason, patent assignment is not recorded with USPTO within three months of its execution, the assignee "stands at risk of having its rights subordinated to a subsequent *bona fide* purchaser or lender acting without notice of the assignment". This is especially important if a patent is to be licensed, sold or asserted, since the patent ownership is the first thing that comes under scrutiny. If, for some reason, a patent transaction is not recorded with USPTO within three months of its execution, there exists a significant risk of the

[22]Full lists can be found at http://www.uspto.gov/ip/boards/foia_rr/resources/patents/pte.jsp and http://www.uspto.gov/learning-and-resources/ip-policy/foia-reading-room/final-decisions-commissioner-patents

transaction being void, if there are any subsequent re-assignements recorded. The Section 261 of the U.S. Patent Act gives this provision:

> An assignment, grant, or conveyance shall be void as against any subsequent purchaser or mortgagee for a valuable consideration, without notice, unless it is recorded in the Patent and Trademark Office within three months from its date or prior to the date of such subsequent purchase or mortgage.

Galasso et al. [2013] note that patent professionals and attorneys strongly advocate for timely recordation of patent ownership transfers [Dykeman and Kopko, 2004, French, 2013]. The direct consequences of unrecorded patent ownership range from unenforceable patent rights and inability to recover damages for infringement in prior to recordation, to loss of rights to use patent-related sales as a bargaining chip in legal proceedings.[23] In an instance of patent owner's death, prompt and proper recordation of patent ownership transfer is further incentivized by the fiduciary duty bestowed upon the person overseeing the financial matters. A fiduciary duty legally obligates an executor, trustee, conservator or person holding the power to act entirely in the best interest of the beneficiaries.[24] Under the US legal system, a fiduciary duty is the strictest recognized standard of care.[25] For example, the Article 8, Section 808 of the Massachussetts Uniform Trust Code holds a trustee personally liable for any breach of fiduciary duty:

> A person who holds a power to direct [a trust] is presumptively a fiduciary who is required to act in good faith with regard to the purposes of the trust and the interests of the beneficiaries. The holder of a power to direct shall be liable for any loss that results from a breach of a fiduciary duty.

[23]In compulsory licensing negotiations, for example. For additional details see French [2013].

[24]Fiduciary duty reaches beyond individual trusts and estates, all the way to corporate boardrooms: the officers and directors of a firm have a fiduciary duty to act in the best interests of the firm and its shareholders by pursuing profits and increasing shareholder value. Interestingly enough, in one of its recent decisions, the Superior Court of Delaware directly linked fiduciary duty and patent monetization by making a statement that corporate officers and directors have a fiduciary duty to the corporation and its shareholders to monetize the corporation's intellectual property (*E.I. Du Pont De Nemours & Co. v Medtronic Vascular, Inc.*, No. N10C-09-058, 2013 WL 1792824, Del. Super., Apr. 24, 2013). This statement, albeit speculative, indicates that courts could hold corporate officers and directors personally liable for lost profits from any "imprudent" use of intellectual property – including a conventional, purely defensive use of patents as a detterent against competitors' legal actions.

[25]Fiduciary duty definition at Legal Information Institute (https://www.law.cornell.edu/wex/fiduciary_duty)

Since fiduciaries are legally required to act in the best interest of the estate or trust beneficiaries, I can assume that US patent ownership transfers resulting from a death of the owner are promptly executed and recorded in the USPTO Patent Assignment Database. This is also noted in a Thomson Reuters FindLaw review on Estate Planning and Intellectual Property:[26]

> A patent application should be filed with the United States Patent and Trademark Office prior to any public use or showing of the invention or sale of the invention. Patents must be transferred in writing. Your will should clearly state who owns the patent, who has the right to license it and who has responsibility for making maintenance payments. In addition, the estate's fiduciary *must* file appropriate documents with the United States Patent and Trademark Office to record the transfer of the patent in order to allow the new owner to administer the patent registration.

Patent owner deaths are identified from patent assignement records in three steps:

1. Words and phrases associated with a owner-related death are identified in assignor, assignee and conveyance text fields. A patent transfer record is labelled as death-related if it contains phrases like "surviving spouse", "widow", "deceased", "death", "testament", "last will", etc.

2. Patent transfers that were executed as a part of employment contract are dropped. These are usually transfers executed before the patent was granted.

3. All patent applications not associated with a granted patent are also dropped.

4. The remaining patent transfers are assumed to be resulting from patent owner death and are used to instrument for PAE activity.

I dichotomize citing entities from my sample into *small* and *large*. This classification comes directly from the USPTO Patent Application Information Retrieval (PAIR) database, where a separate entry indicates whether an applicant qualified for discounted patent filing fees

[26]Beth Silver, Esq. "Estate Planning Issues and Intellectual Property." Thomson Reuters FindLaw. Last accessed April 30, 2015. http://corporate.findlaw.com/law-library/estate-planning-issues-and-intellectual-property.html.

based on its size.[27] The USPTO assigns patent assignees into *small* and *large* according to Small Business Administration (SBA) criteria. The SBA is a United States government agency created in 1953 to provides support and assistance to small businesses. While the size standards for an entity to be classified as small vary accross different industries, the two widely used size standards are 500 employees or less for most manufacturing and mining industries, and $7.5 million or less in average annual receipts for many nonmanufacturing industries.[28]

Public access section of PAIR displays issued or published application status, including the classification of the applicant and the status of the patent. Since USPTO PAIR database dump is not publically available, and USPTO prevents web crawling on PAIR, I use available parts crawled and provided by Google[29] and Reed Tech[30]. This provides me with patent application records for more than 3 million granted patents. While both Google and Reed Tech continuously crawl USPTO PAIR database, there are no intimations that the crawl is somehow prioritized, or that patent records are acquired in a specific order. Some patent records are indeed missing from the crawled database, and some are not up-to-date. I assume these missing points to be completely random since there is nothing about the crawling process employed by Google and Reed Tech that would indicate a presence of systematic bias. Figure 1.2 shows coverage of available USPTO PAIR data, and compares the PAIR data with actual granted US patent counts.[31]

Table 1.1 summarizes four data sources used to synthesize patent data analyzed in this

[27] On March 19, 2013, a provision in the America Invents Act added an additional "micro" category. Since all micro entities are a subset of small entities, I group all entries in this category under small entity status. For more information on entity status determination and filing discounts, see §509.02 at http://www.uspto.gov/web/offices/pac/mpep/s509.html

[28] For details, see SBA size standards webpage at https://www.sba.gov/content/summary-size-standards-industry-sector.

[29] http://www.google.com/googlebooks/uspto-patents-pair.html

[30] http://patents.reedtech.com/Public-PAIR.php

[31] Both Google and Reed Tech simply state that they are "crawling the USPTO Public PAIR (Patent Application Information Retrieval) website and downloading patent documents, including image file wrappers (IFW PDF's)", and that the "crawl operates continually and will be retrieving both already-submitted documents and new documents as the USPTO makes them publicly available."

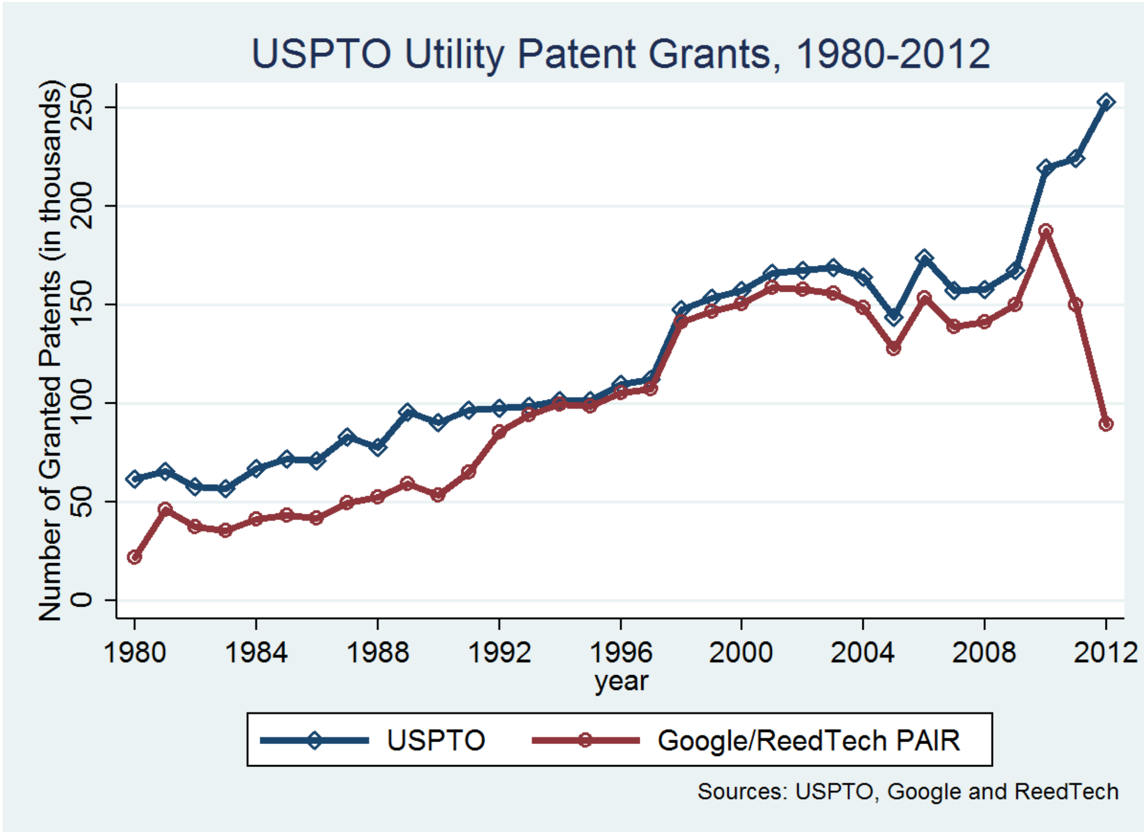

Figure 1.2: *USPTO PAIR Coverage*

paper.

1.4.2 Summary

Tables 1.2 – 1.4 provide summary statistics of the patent data: Table 1.2 summarizes the full patent sample data, Table 1.3 summarizes the enforcable patent sample data, and Table 1.4 summarizes the expired patent sample data. In Tables 1.3 and 1.4, the first citing year is 2001 because they summarize the patent sample used to control for examiner-added citations. Since the USPTO started adding examiner citations data in 2001, citing patent data starts in the same year.

Table 1.1: *Patent Data Sources*

Description	Time coverage	Sources
USPTO Patent Grant Data	1975-2013	NBER, USPTO
USPTO Assignment Data	1980-2013	USPTO
USPTO PAIR Data	1980-2013	Google, Reed Tech
USPTO Maintenance Fees	1981-2013	Google

Table 1.2: *Summary Statistics, All Patents (1982-2012)*

VARIABLES	N	mean	sd	min	max
All Forward Citations	1,682,210	0.927	2.452	0	172
Small Entity Forward Citations	1,682,210	0.218	0.729	0	52
Large Entity Forward Citations	1,682,210	0.572	1.875	0	116
All Forward Citations (w/o Examiner-added Citations)	1,682,210	0.484	1.961	0	102
Small Entity Forward Citations (w/o Examiner-added Citations)	1,682,210	0.0874	0.499	0	36
Large Entity Forward Citations (w/o Examiner-added Citations)	1,682,210	0.293	1.440	0	96
Patent Cohort Year	1,682,210	1994	6.454	1982	2011
Citing Year	1,682,210	2003	6.598	1982	2012
Patent Enforcability Dummy	1,682,210	0.732	0.443	0	1
Death Dummy	1,682,210	0.00827	0.0905	0	1
PAE Dummy	1,682,210	0.00651	0.0804	0	1
Patent Class Categorical Variable	1,682,210	155	76.67	1	263

1.5 Empirical Design

1.5.1 Overview

Endogeneity bias is a serious concern when it comes to estimating the impact of PAE entry on firm behavior. Both targeted firms and technologies are ultimately a part of PAEs strategic choice set, further dependent on some unobservable characteristics of PAE and the target firm. If both PAE activity and firm behavior are correlated with these unobservable characteristics, without a source of exogenous variation, any estimated effect of PAE activity on firm behavior would be biased. For example, fragmentation of patent rights in some technology are may be negatively correlated with firms' propensity to draw

Table 1.3: *Summary Statistics, Enforcable Patents (1982-2012)*

VARIABLES	N	mean	sd	min	max
All Forward Citations	767,491	1.153	2.972	0	128
Small Entity Forward Citations	767,491	0.217	0.781	0	36
Large Entity Forward Citations	767,491	0.720	2.245	0	116
All Forward Citations (w/o Examiner-added Citations)	767,491	0.845	2.627	0	102
Small Entity Forward Citations (w/o Examiner-added Citations)	767,491	0.145	0.656	0	36
Large Entity Forward Citations (w/o Examiner-added Citations)	767,491	0.529	1.956	0	96
Patent Cohort Year	767,491	1999	4.702	1982	2011
Citing Year	767,491	2006	3.345	2001	2012
Patent Enforcability Dummy	767,491	1	0	1	1
Death Dummy	767,491	0.00882	0.0935	0	1
PAE Dummy	767,491	0.0104	0.101	0	1
Patent Class Categorical Variable	767,491	163.6	73.53	1	263

on that technology in their follow-on innovation efforts. At the same time, fragmentation of patent rights could provide plenty of opportunities for PAE arbitrage, ultimately resulting in an increased PAE activity. This would cause simple estimates of the PAE impact to be downward biased, perhaps severly so.

Unbiased causal identification requires PAE activity to vary exogenously. Upstream—or supply-side—shocks are commonly used in econometrics to instrument for and estimate downstream—or demand-side—outcomes [Card, 2001]. I use the death of an individual patent owner to provide a discrete, positive shock to the market supply of patents, and subsquently, the presence of PAEs in the technological area. In other words, my empirical setup considers PAE activity as a *treatment*, and to ensure that treatment assignment is exogenous, I use the death of an individual patent owner and subsequent transfer of patent rights as an assignment mechanism. A somewhat similar empirical strategy has been used by Azoulay et al. [2010] to identify the effect of star scientists' death on the subsequent research output of their coauthors.

PAEs acquire a significant share of patents in their portfolios. Anecdotal evidence and the patent assignment data indicate that the patents transferred after patent owner's death are disproportionately more likely to be transferred or licensed to PAEs. First I create a list

Table 1.4: *Summary Statistics, Expired Patents (1982-2012)*

VARIABLES	N	mean	sd	min	max
All Forward Citations	390,673	0.568	1.735	0	102
Small Entity Forward Citations	390,673	0.142	0.559	0	35
Large Entity Forward Citations	390,673	0.280	1.208	0	98
All Forward Citations (w/o Examiner-added Citations)	390,673	0.425	1.556	0	100
Small Entity Forward Citations (w/o Examiner-added Citations)	390,673	0.0923	0.459	0	35
Large Entity Forward Citations (w/o Examiner-added Citations)	390,673	0.220	1.090	0	96
Patent Cohort Year	390,673	1991	5.375	1982	2008
Citing Year	390,673	2008	3.264	2001	2012
Patent Enforcability Dummy	390,673	0	0	0	0
Death Dummy	390,673	0.0144	0.119	0	1
PAE Dummy	390,673	0.00146	0.0381	0	1
Patent Class Categorical Variable	390,673	145.8	78.88	1	263

of known PAEs and match those entities to patent assignment records, in order to pinpoint patents transferred to PAEs. Then I identify patent transfers associated with the owner-death event, and use them to instrument for PAE patent ownership or *PAE activity* in a 2SLS framework. I create a list of known PAEs and match those entities to patent assignment records, in order to pinpoint patents transferred to PAEs. To estimate the effect of PAE activity, I observe citation patterns of a PAE-acquired patents and identify changes in those patterns after PAEs acquire those patents.

1.5.2 Patent Owner Deaths

My instrumental variable exploits the fact that the passing of the patent owner is completely exogenous to PAE activity. While it is certainly plausible that PAE may want individual patent owners to "go away" so that they can acquire their intellectual property, to this day, it has not been shown that a PAE has been responsible for any known deaths of individual patent owners, either directly or indirectly.[32] The exclusion restriction requires that the

[32]This is not entirely true when it comes to large, practicing entities. In 1954, after being expropriated by RCA and worn down by years of legal wrangling over his FM patents, Edwin H. Armstrong, one of most prolific inventors in the history of radio, commited suicide by jumping from the thirteenth floor of his New York City

passing of the patent owner impacts firm behavior *only* through the litigious activity of PAEs. A potential problem may arise if the firms exposed to PAE activity monitor the environment carefully and are able to observe patent owner death before a patent gets transferred to PAE. If so, then it would then be conceivable to see these firms adjust their behavior and strategy *before* PAEs acquire relevant patents. However, because the average time between owner death and PAE patent acquisition in my sample is only 0.83 years, it is hardly plausible that, even if firms indeed monitored life events of individual patent owners, they would have enough time to respond before PAEs take over. Finally, patents transferred after patent owner's passing are almost 6 times more likely to be transferred or licensed to PAEs, than other patents in my sample. In comparison to all other patents' PAE transfer rate of 0.7% in my data, out of 1,393 recorded individual patent owner deaths, 54 were transferred to PAEs, resulting in transfer rate of almost 4%. While these numbers are seemingly small, they should not have an econometric impact on the instrument validity. If anything, they put significantly more pressure on the instrument and the first stage in the two-stage estimation process, because of the reduction in the sample size. This illustrated in Table 1.5 which shows proportions of trolled and "death-related" patents to all other patents in the sample.

Table 1.5: *Deaths and Patent Transfers (1981-2012)*

Number of patents transferred to PAEs	755
Number of all patents transferred *after owner death*	1,393
Number of patents transferred to PAEs *after owner death*	54
Total number of patents in the sample	113,053
Percentage of patents transferred to PAEs *after owner death*	3.88%
Percentage of all other patents transferred to PAEs	0.63%
Ratio of patents transferred to PAEs *after owner death* to all other patents transferred to PAEs	5.80

Anecdotal support for the instrument is also strong. For example, after Dr.William

apartment. The story goes that, upon hearing about Armstrong's death, then head of RCA and Armstrong's arch nemesis, David Sarnoff immediately exclaimed: "I did not kill Armstrong." After Armstrong's death, his widow was awarded millions of dollars in royalties due to her from RCA and other companies [Schwartz, 2003].

Howard Waugh, an accomplished physician, professor, and inventor passed away[33], his estate transferred the rights to two of his patents to the Tawsaura Group LLC.[34] These patents covered the composition and delivery of the L-Citrulline.[35] Within two weeks from acquiring Dr.Waugh's patents, the Tawsaura Group filed patent infringement lawsuits against 36 firms in dietary supplement industry. In a little bit over a year, the Tawnsaura Group has filed 91 lawsuits using these two patents. Similar examples can be found in other intellectual property classes: in 1842, Henry Wall, often referred to as the first copyright troll, started collecting fees for unauthorized performances of songs, mostly by acquiring copyrights from estates of deceased composers [Deazley et al., 2010].

Patent Assertion Entitity Activity

While coming up with a general definition of an PAE is not exceptionally difficult, operationalizing that definition, and identifying PAEs amongst millions of enterprizes in United States is a much harder task.[36] Labelling a business as an PAE can be somewhat controversial, because of largely negative connotations associated with PAE business models and their highly litiguous behavior.[37] To address the problem so far, the academic literature has utilized various approaches, from custom databases created via internet and news searches [Reitzig et al., 2010, Shrestha, 2010, Fischer and Henkel, 2012, Jeruss et al., 2012] to

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[33]Dr. William Howard Waugh's obituary at the American Physiological Society: http://www.the-aps.org/mm/Membership/Obituaries/Waugh.html (last accessed on 10/10/2014).

[34]According to the offical State of Nevada business database portal, the Tawnsaura Group was incorporated in Reno, Nevada only one month before Dr. Waugh's death. Public records show only one employee listed for Tawnsaura, the same trial attorney also representing Tawnsaura in every one of its 91 patent infingement lawsuits. To date, there are no records of Tawnsaura doing any type of R&D, no records of it ever manufacturing any products, and no records of it ever patenting any original inventions anywhere in the world.

[35]L-Citrulline is a naturally occuring amino acid used to improve exercise performance and a widely distributed dietary supplement

[36]US Census Bureau puts the number of business in USA at around 30M (http://www.census.gov/compendia/statab/2012/tables/12s0744.pdf)

[37]During the course of the *Lumen View Technology, LLC v Findthebest.com, Inc.* legal proceedings, Lumen View's attorney even implied that the Findthebest.com's CEO committed a hate crime under Ninth Circuit law by using the term "patent troll".

data dumps from third-party providers[38] [Bessen et al., 2011, Cohen et al., 2014, Mazzeo et al., 2014]. Opacity of most PAEs, hundreds of shell companies under their control, and lack of readily accessible public data render an agnostic and methodologically consistent approach to identifying PAEs almost impossible. To get around this, I combine data acquired from internet and news searches with RPX PAE list, Plainsite PAE list[39], and 10-K filings from a handful of publically traded PAEs. From this list, I remove all universities, university affiliated foundations and entities with a significant number of original patents (like Qualcomm, for example). My final list consists of 2,776 entities classifed as PAEs.

To identify patents transferred to PAEs, I run a customized version of NBER company name standardization routines on patent assignors and assignees in USPTO reassignment records, and on the names of all PAE entities in my list [Hall et al., 2002]. I then match standardized PAE names to USPTO assignor and assignee names to identify all patents transferred to PAEs. I use only direct entity name matches in the process, which allows me to identify a sample of 755 patents transferred to PAEs.

Outcomes

My main dependent variable is the number of forward citations received by the focal patent in a year t. Some of these citations are made by the patent applicants themselvels and some are added by the patent examiner during the patent examination process [Alcacer et al. 2006, 2009]. To account for this dichotomy, and to address potential concerns about the impact of patent examiners, I separate forward citations in two groups: those made by *patent examiners* and those made by *patent applicants*. In addition, I also split forward citations in those received by *small* and *large* entities to examine the heterogeneity of firm response to PAE activity.

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[38]Bessen et al. [2011] use RPX PAE database, Cohen et al. [2014] use PatentFreedom PAE database and Mazzeo et al. [2014] use PricewaterhouseCoopers data.

[39]Created through crowdsourced efforts. For more information, see http://www.plainsite.org/tags/patent-trolls/

1.5.3 Specification

Estimation of the impact of PAE activity on firm citation patterns presents some interesting econometric challenges. These stem from two facts: the first being that my ultimate dependent variable—patent citations—is a non-linear count measure, and the second being that the endogenous regressor is binary variable. Accounting for endogeneity with the two-stage instrumental variable estimation becomes quite complex when either the first or the second stage relationship is non-linear. I use linear 2SLS as the primary specification, even though the ultimate relationship is non-linear. The use of linear IV framework in this particular instance can be justified by several arguments. First, the linear IV specification should capture the treatment effect analogue to LATE for dummy endogenous regressors, even with the non-linear second-stage relationship [Angrist, 2001, Angrist and Krueger, 2001, Angrist and Pischke, 2009, Cameron and Trivedi, 2013]. Second, using a non-linear first stage estimation places a lot of weight on getting this functional form just right, and risks introducting significant bias and making estimates difficult to interpret if the first stage happens to be incorrectly specified. Finally, a linear 2SLS framework generally results in estimates that are resonably close to minimum-mean-squared-error linear approximations of non-linear conditional expectation functions [Angrist and Pischke, 2009]. Because I am interested in a causal effect of the PAE patent acquisition and would like to know how citation patterns change over having a precisely estimated parameter, 2SLS framework is econometrically adequate approach to take. As a robustness check, I also run instrumental variable Poisson regression using a control-function approach to control for the endogeneity of PAE patent acquisitions. This approach utilizes Method-of-Moments framework and uses residuals from the first-stage linear regression of endogenous regressor on instrumental variable to control for the endogeneity in the second-stage Poisson regression [Newey, 1984, Wooldridge, 2010].

1.5.4 Linear IV

The first stage assesses the relationship between the instrument, in this case being a patent owner death, and the endogenous regressor, in this case being PAE activity:

$$PAE_{p,t} = \alpha_0 + \alpha_1 \times Death_{p,t} + Class^{'}_p + Cohort^{'}_p + Year^{'}_p + \nu_{p,t} \tag{1.1}$$

where i denotes USPTO main patent class, t denotes citing patent application year, a denotes cited (focal) patent application year (cohort year), NPE is a binary dummy that denotes an PAE appearing as an assignee in the USPTO reassignment record, $Death$ is a binary dummy that denotes the patent owner death-related transfer, $Class$ and $Year$ denote patent class and citing year fixed effects, and $Cohort$ denotes the patent cohort year fixed effects. While the temporal lag of patent citations generally follows log-normal distribution (as illustrated in Figure 1.3), to capture the systematic variations of patenting and patent-citing practices over time, $Cohort$ and $Year$ control for both the application year of the cited patent and the application year of the citing patent. The first effect is usually referred to as the "cohort effect" and was shown to have a significant impact on the citation profile of a patent [Hall et al., 2002]. Frequent patent policy changes at the USPTO affecting both quantity and quality of granted patents are the main culprit behind the "cohort effect". The second effect is usually referred to as the "calendar effect" and is caused by the systematic increase in the number of citations per patent over time [Hall et al., 2002]. The patent class fixed effects $Class$ controls for the heteregeneity in citing practices across technology classes.

I assume errors to be random and orthogonal to other independent variables in the regression:

$$\mathbb{E}[\nu_{p,t} | Class, Cohort, Year, Death] = 0 \tag{1.2}$$

The second stage regresses predicted PAE activity on the patent citation measure to estimate a causal impact of PAE activity on knowledge flow patterns:

$$y_{p,t} = \beta_0 + \beta_1 \times \hat{PAE}_{p,t} + Class^{''}_p + Cohort^{''}_p + Year^{''}_p + \epsilon_{p,t} \tag{1.3}$$

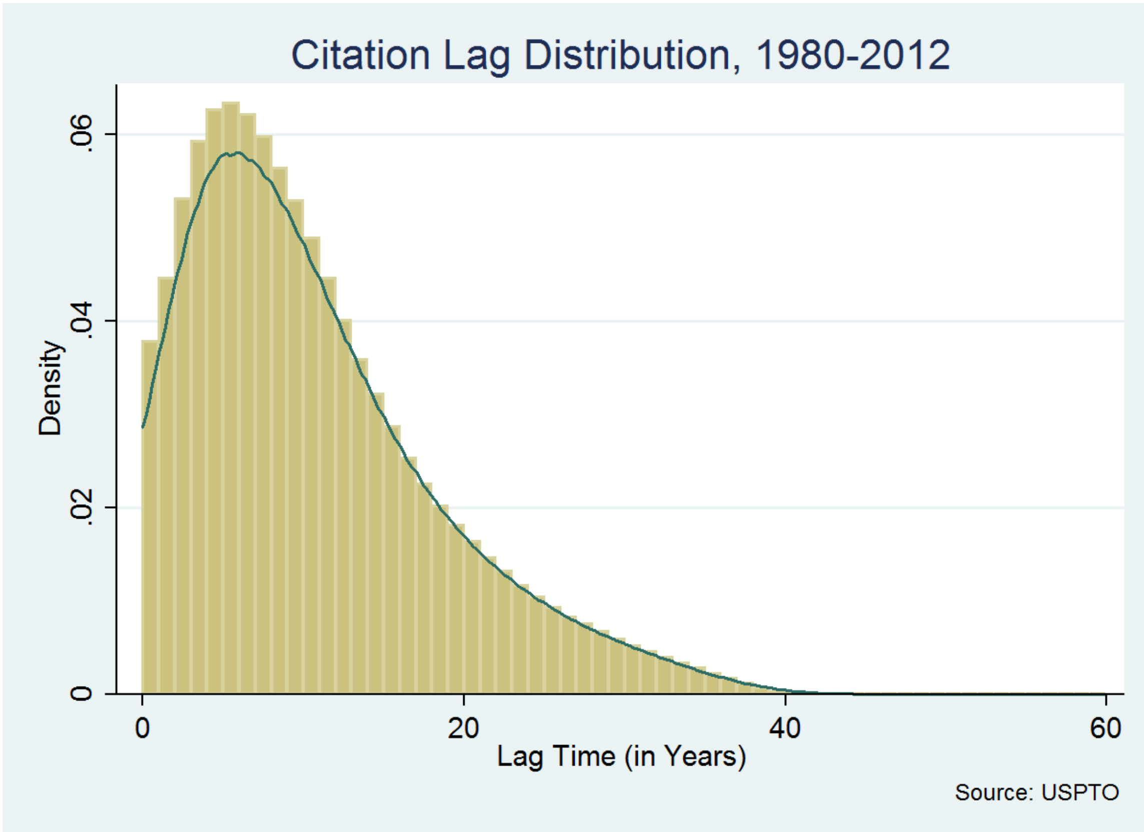

Figure 1.3: *Temporal Distribution of Patent Citations*

where y denotes the outcome variable represented as a number of focal patent forward citations received in a year t , $P\hat{M}E$ denotes the predicted PAE activity from the first-stage estimates, $Class$ and $Year$ denote patent class and citing-year controls, and $Cohort$ measures the patent cohort fixed effects. For identification, it is necessary that the $Death_{p,t}$ and $\epsilon_{p,t}$ are uncorrelated conditional on the covariates, and that $Death_{p,t}$ is sufficiently strong in predicting $PME_{p,t}$. To allow all patents in my sample to freely correlate within a patent class and over time, standard errors are clustered on the three-digit USPTO patent class level.

1.5.5 Poisson Regression

For robustness check of 2SLS specification, I also run an instrumental variable Poisson regression with the control function estimator. This estimation strategy maintains the exponential nature of the dependent variable and relies on the multiplicative error model. The underlining relationship can be expressed as:

$$y_{p,t} = \exp(\beta \times PAE_{p,t} + Class_p + Cohort_p + Year_p)\epsilon_{p,t} \tag{1.4}$$

where $PME_{p,t}$ is an endogenous PAE activity parameter that can be estimated as:

$$PAE_{p,t} = \alpha \times Death_{p,t} + \varepsilon_{p,t} \tag{1.5}$$

The main error term is then decomposed as:

$$\epsilon_{p,t} = \exp(\rho \times \varepsilon_{p,t} + k_{p,t}) \tag{1.6}$$

Finally, the conditional mean model for y is estimated by first estimating ε vector, and then additing it as additional regressor to control for endogeneity:

$$\mathbb{E}[y|PME, \kappa, \phi, \lambda, u] = \exp(\beta \times PME_{p,t} + Class_p + Cohort_p + Year_p + \rho \times \varepsilon_{p,t}) \tag{1.7}$$

From this, we can define error functions for the endogenous PAE activity and the dependent variable as:

$$u_{PME}(PME, Death, \alpha) = PME_{i,t} - \alpha \times Death_{p,t} \tag{1.8}$$

$$\begin{aligned} &u_y(y, PME, Class, Cohort, Year, \alpha, \beta, u_{PME}) \\ &\qquad = \frac{y_{p,t}}{\exp(\beta \times PME_{p,t} + Class_p + Cohort_p + Year_p + \rho \times \varepsilon_{p,t})} - 1 \end{aligned} \tag{1.9}$$

In turn, these give us population mean conditions:

$$\mathbb{E}[Death \times u_{en}] = 0 \tag{1.10}$$

$$\mathbb{E}[(PME, Death, \hat{\varepsilon}) \times u_y] = 0 \tag{1.11}$$

Which allow us to use GMM to estimate coefficients on PAE activity. However, Poisson coeffients may be difficult to interpret in this particular context and will be utilized as a robustness check only.

1.6 Results

1.6.1 Main Results

Tables 1.6-10 present the main results of this study. Table1.6 shows the results on the overall number of citations for the full sample of US patents 1981-2012: endogenous OLS regression is in the first column, reduced form regression in the second column, IV 2SLS regression in the third column and IV Poisson regression in the fourth column.

The sample covers all granted patents from the same patent classes and cohorts as the patents impacted by the instrument. This set of regressions does not control for examiner-added citations, since these were added to the data starting in 2001. In addition, these regressions do not take into account patent expiration dates, and include all patent citations, regardless of the cited patent enforcability status. Interestingly enough, the PAE activity coefficient in is positive and significant in the endogenous regressions, and would suggest that, after being acquired by PAEs, patents would stand to gain about 0.43 citations, or about 3% of all citations on average. However, the same coefficient is negative and signficant in the instrumented 2SLS regressions, indicating a loss of 2.6 citations, or approximately 17% of all citations on average . This points to the presence of bias in endogenous regression, and suggests that, because PAEs endogenously select which patents to acquire and how to utilize them, simple OLS is not an appropriate analytic tool. This is exactly the shortcoming

Table 1.6: *All Forward Citations, 1981-2012*

VARIABLES	Endogenous OLS	Reduced Form OLS	IV 2SLS	IV Poisson
	(1)	(2)	(3)	(4)
Patent Owner Death		-0.102**		
		(0.044)		
PME Activity	0.431**		-2.603*	-1.763
	(0.204)		(1.468)	(1.528)
Citing Year Fixed Effect	Yes	Yes	Yes	Yes
Application Year Fixed Effect	Yes	Yes	Yes	Yes
Patent Class Fixed Effect	Yes	Yes	Yes	Yes
Constant	0.0234	0.0221	0.526*	-2.986***
	(0.0375)	(0.0377)	(0.316)	(0.159)
1st Stage F-statistic	-	-	7.85	-
Observations	1,682,210	1,682,210	1,682,210	1,682,210
R-squared	0.0845	0.0844	0.0811	

Standard errors, clustered at 3-digit USPTO patent class level, in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

I'm trying to adress via instrumental variable approach. While statistically insignificant and difficult to interpret in this context, IV Poisson regression coefficient is also negative and provides additional support for IV 2SLS results.

1.6.2 Patent Examiner Effects

In Section 3, I elaborated on the impact patent examiners have on citation patterns. Since examiners have been shown to add a significant number of patent citations, and could raise the noise floor in my analysis, I ran a separate set of regressions without examiner-added citations to ensure that PAE activity effects are measured with respect to patent applicant behaviour only. Since information about examiner-added citations is available through USPTO patent grant data starting in 2001, I use a sample of patents applied for in 1981 and later, but observe only those citations made on or after 2001. Tables 1.7 and 1.8 compare results with and without examiner-added citations for both small and large entities.

Table 1.7: *Large Entity Examiner-added Citation Effects, 2000-2012*

	With Examiner-added Citations		Without Examiner-added Citations	
	IV 2SLS	IV Poisson	IV 2SLS	IV Poisson
VARIABLES	(1)	(2)	(3)	(4)
NPE Activity - Large Entities	-3.339**	-6.481*	-2.449**	-5.627*
	(1.515)	(3.595)	(1.189)	(3.532)
Citing Year Fixed Effect	Yes	Yes	Yes	Yes
Application Year Fixed Effect	Yes	Yes	Yes	Yes
Patent Class Fixed Effect	Yes	Yes	Yes	Yes
Constant	-0.0772	-2.123***	-0.0705	-2.770***
	(0.177)	(0.077)	(0.184)	(0.082)
1st Stage F-statistic	7.86	-	7.86	-
Observations	1,152,784	1,152,784	1,152,784	1,152,784
R-squared	0.076	-	0.067	-

Standard errors, clustered at 3-digit USPTO patent class level, in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

In both tables, columns (1) and (2) show results of IV 2SLS and IV Poisson regressions for all forward citations, including examiner-added citations. Columns (3) and (4) show results of IV 2SLS and IV Poisson regressions without examiner-added citations. Within-entity comparison of results for with- and without-examiner-added citations indicates that examiners do not play a significant role for PAE activity-induced effects, and that firm behavior is almost exclusively responsible for the observed effects. For large entities, if we take examiner-added citations into account, I estimate that PAE acquisition of a patent leads to 3.3 lost citations, or about 22% of all citations on average. If examiner-added citations are removed, then the effect magnitude decreases only slightly to 2.4 lost citations, or 16% of all citations on average. For small entities, that change is even smaller: with examiner-added

Table 1.8: *Small Entity Examiner-added Citation Effects, 2000-2012*

	With Examiner-added Citations		Without Examiner-added Citations	
	IV 2SLS	IV Poisson	IV 2SLS	IV Poisson
VARIABLES	(1)	(2)	(3)	(4)
NPE Activity - Small Entities	1.0581*	10.381**	0.8287*	12.237**
	(0.6179)	(4.795)	(0.4955)	(5.608)
Citing Year Fixed Effect	Yes	Yes	Yes	Yes
Application Year Fixed Effect	Yes	Yes	Yes	Yes
Patent Class Fixed Effect	Yes	Yes	Yes	Yes
Constant	0.1579***	-1.026***	0.0632**	-1.721***
	(0.0417)	(0.128)	(0.0266)	(0.137)
1st Stage F-statistic	7.86	-	7.86	-
Observations	1,152,784	1,152,784	1,152,784	1,152,784
R-squared	0.061	-	0.040	-

Standard errors, clustered at 3-digit USPTO patent class level, in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

citations, PAE-acquired patents gain 1.1 citation or 7.3% of all citations on average, while without examiner-added citations, they gain 0.8 citations or 5.3% of all citations on average. Estimates are equally as close for Poisson regressions: -6.5 vs. -5.6, and 10.38 vs. 12.24 for large and small entities, respectively.

1.6.3 Active vs. Expired Patents

Since I expect to see effects of PAE acquisitions manifest themselves only while acquired patents are enforceable I also compare the periods before and after patents expire. This analysis is done without examiner-added citations on all patents applied on or after 1981, and forward citations made on or after 2001. Tables 1.9 and 1.10 show these results.

Results for large entites are given in Table 1.9. PAE acquisition causes a patent to lose on average 5.8 or 38.6% of all citations coming from large entities while it is enforceable,

Table 1.9: *Active vs. Expired Patents, Large-Entity-only Citations, 2000-2012*

	With Examiner-added Citations		Without Examiner-added Citations	
VARIABLES	IV 2SLS (1)	IV Poisson (2)	IV 2SLS (3)	IV Poisson (4)
NPE Activity - Small Entities	1.0581*	10.381**	0.8287*	12.237**
	(0.6179)	(4.795)	(0.4955)	(5.608)
Citing Year Fixed Effect	Yes	Yes	Yes	Yes
Application Year Fixed Effect	Yes	Yes	Yes	Yes
Patent Class Fixed Effect	Yes	Yes	Yes	Yes
Constant	0.1579***	-1.026***	0.0632**	-1.721***
	(0.0417)	(0.128)	(0.0266)	(0.137)
1st Stage F-statistic	7.86	-	7.86	-
Observations	1,152,784	1,152,784	1,152,784	1,152,784
R-squared	0.061	-	0.040	-

Standard errors, clustered at 3-digit USPTO patent class level, in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

but that effect completely disappears once the patent expires. Results for small entities are shown in Table 1.10 and indicate that, while PAE acquistion leads to a small increase in citations from small entiries, that result is not statistically significant. This would indicate that large entities are trying to minimize assertion risk by citing PAE-acquired patents less, and especially doing so while these patents are active.

1.6.4 Small vs. Large Firms

The heterogenity in firm response to PAE activity is apparent from Tables 1.7 – 1.10. Large firms strongly avoid citing PAE-acquired patents, especially while these patents are enforcable. Enforcable patents acquired by PAEs stand to lose anywhere between 22%-39% of its forward citations coming from large entities. On the other hand, small entities weakly increase their citations of PAE-acquired patents, or remain completely indifferent. Enforcable

Table 1.10: *Active vs. Expired Patents, Small-Entity-only Citations, 2000-2012*

	Active Patent		Expired Patent	
	IV 2SLS	IV Poisson	IV 2SLS	IV Poisson
VARIABLES	(1)	(2)	(3)	(4)
NPE Activity - Large Entities	-5.826**	-13.434**	0.479	3.719
	(2.465)	(5.844)	(0.980)	(5.904)
Citing Year Fixed Effect	Yes	Yes	Yes	Yes
Application Year Fixed Effect	Yes	Yes	Yes	Yes
Patent Class Fixed Effect	Yes	Yes	Yes	Yes
Constant	-0.172	-2.391***	-0.0176	-2.316***
	(0.185)	(0.00925)	(0.0490)	(0.0832)
1st Stage F-statistic	9.02	-	5.03	-
Observations	767,491	767,491	390,673	390,673
R-squared	0.041	-	0.058	-

Standard errors, clustered at 3-digit USPTO patent class level, in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

patents acquired by PAEs stand to gain anywhere between 5%-7% of its forward citations coming from small entities.The results are consistent with the previous work in this area and confirm the hypothesis that large firms are likely to be strategic in the patent space.

1.7 Discussion

While the results confirm hypothesis that large entities strategically avoid exposure to PAE activity, the study does have several shortcomings that warrant additional discussion. First of all, the econometric approach of estimating a non-linear function with a linear model may not be fully optimal. While the second set of results obtained via Poisson regression is fully alligned with the linear IV results, and provides a hefty dose of confidence in the linear model, the concerns about the magnitude of estimated parameters still linger. Although there should be no doubt about the direction of the effect, the quest for more precisely estimated parameters may require additional work, and a custom estimating routine to be developed. Second, we may be concerned with the fact that patents transferred because of patent owner death are all individual inventor-owned patents, and may be fundamentally different from other patents in the sample. USPTO does track and classify intial patent assignees, but unfortunately leaves a significant number of patents classified as "unassigned" or "not known". Thus, running a regression on individual inventor-owned patents only would 1) introduce a lot of noise into the system and 2) significantly reduce sample size to the point where statistical power would certainly suffer. Although not reported in this paper, as a robustness check, I ran 2SLS regressions with an independent variable dummy for individually owned patents that could be identified from the USPTO data, and noticed no significant change in PAE effects on follow-on citations.[40] If anything, the magnitudes of estimated parameters showed a slight increase after individually-owned dummy was included. On a related note, Roach and Cohen [2013] identify private knowledge flows such as consulting projects, contract work and conferences as a mechanism that could impact citation counts. While it is certainly possible that a death of an individual inventor could be a confounding factor, and lead to a subsequent drop in citations caused by the absence of private knowledge flows, the fact that estimated negative effect of PAE activity on future citations by large entities dissapears after the patent in question expires, suggests that private knowledge flows are most likely not the main cause behind the estimated "PAE effect." Also, the observed ex-post increase in citations by small entities counters this theory.

A different, but equally as important concern has to do with the broader effects of PAE activity on cumulative innovation. While I measure direct effects on citation patterns of PAE-acquired patents, I do not measure effects on broader patent classes, and cannot say much about possible adjustment in firms' technology search patterns. Similar to Galasso and Schankerman [2015], one could create a set of technologically proximate, matching patents to see if there exists a "substitution effect", i.e. whether large firms strategically avoid *only*

[40] These results are available upon request

PAE-owned patents while still citing closely related patents, or they avoid techonologies plagued with PAEs alltogether. If so, then the advent of PAEs could have more profound effects on the follow-on innovation. However, because the negative effects on citations of PAE-owned patents go away after they expire, this lends support for purely strategic avoidance of these patents by large firms. Lanjouw and Schankerman [2001] find that litigated patents exibit a "publicity effect"—once they are litigated, they become more visible to both examiners and applicants, and get cited more as a consequence. While PAEs litigate many of their patents, I do not observe this "publicity effect" for the large firms. Citations made to PAE-owned patents by small firms do increase, and publicity effect may have something to do with that. Because small firms have less options and less resources to avoid interacting with PAEs, it is likely that either they are being strategic and trying to signal that PAE-owned patents are different from or inferior to the current invention, they are already been targeted and are licensing PAE-owned patents, or PAE-owned patents become more visible and acquire more forward citations by small firms. This state of the world can have a nefarious undertone: if PAE presence is forcing small firms to focus their attention on a small set of patents and technologies, that could negatively impact creativity and overall inovativeness of these firms. Since the propensity of small firms to cite PAE-owned patents does not change much pre- and post-expiry, it is hard to make an argument for a clear strategic intent here. If small firms were indeed citing PAE-owned patents only to minimize their hold-up risk, then after those patents were to expire, citations by small firms should decrease. However, the coefficients on citations to PAE-owned patents made by small firms pre- and post- expiry stay remarkably similar.

Finally, while this is one of the first studies to examine the effect of patent term expiration on forward citations, patent term lengths for those patents maintained through the full term are only approximated. Patent term adjustments and extensions implemented by the USPTO are not added to the patent term calculations, and should be included to precisely estimate these effects in the future. In addition, since the statute of limitations for initiating patent infringement lawsuits extends for up to 6 years after the patent expires, this could introduce additional lag into the citation patterns.

1.8 Conclusion.

One of the key arguments for a "benevolent troll" hypothesis is that PAEs reduce search costs and identify technological relationships otherwise difficult to detect. In this world, potential customers who would benefit from rights to technologies owned by patent trolls are identified and patents are licensed to them, with or without legal action. Patent license execution usualy sends a signal about the commercial value of licensed technology to the market and should lead to increased follow-on research, resulting in higher ex-post citation rates. Indeed, previous studies have found that citations to licensed patents by both non–licensees and licensees increased after the licenses were executed [Sampat and Ziedonis, 2005, Drivas et al., 2014]. Following this line of logic, if the trolling strategy was truly efficiency-enhancing, we would expect to see citations to troll-acquired patents to increase after the acquistion, regardless of the citing entity type. While this happens to be true for the small firms, the trend is completely opposite for the large firms. Since large firms are more strategic in their behavior, this leads me to conclude that a risk of a PAE lawsuit drives these firms to reduce citations to PAE acquired patents. Given that this is the first study that attempts to tease-out the causal effects of PAEs on the firm behavior, even though the results may not be directly translatable into policy-actionable outcomes, they undoubtely indicate that firms react to PAE patent acquisitions in the knowledge space. A more detailed follow-on work is needed to tease out if the changes in citation patterns are only strategic, or they indeed point to serious disruptions in cumulative innovation patterns. The results of this study also raise some concerns about "inequitable conduct" policy and its effectiveness in preventing strategic citations of prior art.

This study also brings attention to empirical strategies we can employ to identify and answer important questions relevant to the intellectual property policy. While showing a lot of promise, the use of upstream market shocks in markets for patents as instrumental variables has gone underutilized for many years. The quest for understanding the intricacies of the value chain in markets for patents could open the doors for causal identification in an area plagued by endogenous choice bias, and stands out as an important area to be studied in the future.

Chapter 2

The Standard-Pool Interface[1]

2.1 Introduction

Technological standards have become an unavoidable part of modern life.[2] Today, the interoperabilty of high-tech devices in complex networks and systems hinges on standardization of interfaces, communication protocols and processes. The welfare-enhancing effects created by standardization can be significant, especially in those markets where this interoperability is important[3] and strong network-effects persist [Farrell and Saloner, 1985]. Standardization can occur through direct market competition to create *de facto* standards, or via regulatory intervention.[4] Most modern standards, however, are created with assistance of standard-setting organizations' (SSOs) driven consensus, and involve voluntary participation and collaboration of many different entities: firms, government agencies, individuals, academic institutions and research laboratories. Regardless of whether these entities are *downstream* manufacturers and service providers, or are *upstream* technology developers, their involve-

[1] Co-authored with Josh Lerner and Jean Tirole

[2] For example, as far back as one decade ago, in their discussion of *Wi-Fi* technical standard, the American National Standards Institute (ANSI) proclaimed that *"just about everything associated with a computer, especially those connected to the Internet, is based on an industry standard."*[ANSI, 2004]

[3] Mobile communications are a good example.

[4] An example of *de facto* standard would be IBM PC, and an example of a standard driven by regulatory intervention would be HDTV standard. For additional discussion, see Lemley [2002] or Greenstein and [eds.].

ment in the standardization process, and in particular their willingness to disclose and license standard-essential patents (SEPs) are crucial for standard implementation, and its success later on. SSOs play a pivotal role in this process, act as a consensus-making body and provide regulatory checks guiding the behavior of participating members. One of the most important regulatory duties of SSOs is to ensure that concerns about ex-post hold-up are minimized through proper disclosure of SEPs, and to facilitate reasonable licensing commitments made by patent owners.

The hold-up in standard-setting usually comes in one of the two flavors. In the first variant, a firm making a RAND or FRAND licensing commitment ex-ante can decide to capitalize on the vagueness of the term "reasonable" and attempt to extract unreasonably high royalty payments ex-post. A recent high-profile legal battle between Microsoft and Motorola illustrates this issue remarkably well. In this case, Microsoft accused Motorola of breaching their RAND commitments made when disclosing SEPs to two different standards: IEEE 802.11 and ITU-T H.264.[5] Microsoft has been widely using these standards in many of their flagship products, including videogame console Xbox 360 and Windows software, and implicated Motorola in requesting unreasonable royalties for their SEPs. The Federal District Court sided with Microsoft and reduced royalties due to Motorola to $1.8M per year from almost $4B per year as originally sought by Motorola. In addition, the court ordered Motorola to pay $14.5M back to Microsoft in compensatory damages. However, the case did remain in court for more two years, and was very costly to resolve. While this type of conduct in standard-setting is not completely uncommon[6], it may require a substantial change in patent disclosure policy and imposition of structured price commitments by patent owners to improve ex-post outcomes.[Lerner and Tirole, 2015]

In the second variant, ex-post hold-up can arise when patent owners strategically underdisclose their patents, as to avoid RAND/FRAND provisions. The case of Rambus is

[5]See *Microsoft Corp. v. Motorola Inc.*, 696 F.3d 872 (9th Cir. 2012)

[6]See *Broadcom Corp. v. Qualcomm Inc.*, 501 F.3d 297, 310 (3d Cir. 2007)

a prime example.[7] Rambus failed to disclose its existing DRAM related patents and patent applications during a standard-setting process at JEDEC SSO, and took care to suspiciously amend some of its patent applications to read on the standard more closely. This kicked off a series of lawsuits that plagued the DRAM industry for more than a decade.[8]

Rapid pace of technological convergence, especially in IT-related fields, allots large economic value to standards. With a large potential upside and an equally as large potential downside, it is logical to expect participating firms to be highly strategic. Given the far-reaching economic impact of standardization, and the potential for strategic gaming and hold-up by profit-maximizing entities, the setting of optimal disclosure and patent licensing policies becomes ever increasingly important. Before we can inform policy, we need to understand exactly how disclosure process works in standard-setting contexts.

This paper analyzes selection mechanisms in technical standards and is focused on the premise that upstream and downstream patent owners have heterogenous patent disclosure strategies. We evaluate patent disclosures made to seven large SSOs, and find that, consistent with theoretical predictions, both downstream and upstream firms act to maximize their ex-post rents. More specifically, we show that downstream firms are more likely to disclose lower-quality patents to standard-setting organizations, and prefer to use generic patent disclosures over specific ones. There are several reasons for such behavior. First of all, large firms with broad patent portfolios have to contend with costly patent searches when making specific disclosures. More importantly, firms with large downstream presence usually do not participate in standard-setting efforts with large licensing revenue in mind. Rather, they are incentivized in fomenting downstream adoption of their technology, and subsequently do not have immediate legal concerns that would force them to make specific patent disclosures. Although it is growing, the quantitative empirical literature about strategic behavior in standard-setting contexts remains relatively scarce. On a theoretical side, Lerner and Tirole [2006] use a "forum-shopping" framework to show that technology owners will choose the

[7]See Complaint, *In re Rambus Inc.*, No. 9302 (F.T.C. June 18, 2002)

[8]Wikipedia article on Rambus-related lawsuits: http://en.wikipedia.org/wiki/Rambus#Lawsuits

friendliest SSO to have their technology adopted by the downstream users. Their model shows that this particular type of forum-shopping may attenuate distributional conflicts, if competing firms end up choosing different SSOs. From an empirical side, Simcoe et al. [2009] investigate the patent disclosure strategies to SSOs, link them to ex-post patent litigation, and show that they heterogenously impact small and large-firms' incentives to litigate. In other related studies, Axelrod et al. [1995] examine firm choices to join standardization alliances, conditional on the firm size and the presence of close competitors in those alliances, and Simcoe [2012] shows that strategic rent-seeking behavior of individual participants can lead to delays in standard-setting process, especially when commercialization pressures are high.

Our study contributes to several other strands of literature. It directly extends the work of Lerner and Tirole [2014, 2015], who lay the groundwork for the analysis of standard-essential patent disclosures made during standardization process. They show that simple FRAND patent licensing commitments create opportunities for strategic behavior of patent owners, only to induce outcomes that are ex-post inefficient. When it comes to patent disclosures, we show that patent owners indeed behave strategically and that asymmetric information presents a problem that SSOs need to consistently grapple with.

The paper is organized as follows: Section II describes technical standards and firm disclosure strategies. Section III describes and summarizes the data, presents the hypotheses, empirical specification and the results. Section IV concludes the paper.

2.2 Technical Standards and Disclosure Practices

2.2.1 Background

As a set of one or more technical specifications, technical standard codifies a collection of common design rules for a product or a process.[9]

[9] According to the National Technology Transfer and Advancement Act (NTTAA), the term "standard" or "technical standard" includes all of the following: (1) Common and repeated use of rules, conditions,guidelines or characteristics for products or related processes and production methods, and related management systems

Standards have many flavors and can emerge in a mulitude of ways. Some are developed privately by a single entity: a firm or government, for example. However, coordinated standard development through SSOs is more common these days. SSOs usually combine a set of very diverse inputs and develop market-driven voluntary standards, which sometimes get mandated via government intervention. In the course of the standard-setting process, SSOs play several critical roles: they identify multiple paths towards a technological solution, they coordinate on one approach among conflicting alternatives and regulate the behavior of members. One of the most important issues under the aegis of SSOs is ensuring that firms disclose relevant patents and agree not to price licenses to their patents too aggressively. Largely due to high coordination costs, sizeable SSOs like ETSI or IEC usually require all of their members and participants to disclose any patents they believe may be standard-essential. This disclosure requirement serves multiple purpose: it directs standard-setting process to take note of disclosed technologies, it forces disclosing parties to make licensing commitments (usually concurrent with the disclosure), it sends the signal to the market about the potential implementation cost down the line, and it provides valuable information for legal authorities in case of a dispute. These disclosure policies vary across different SSOs, and are usually difficult to change once set.[Bekkers and Updegrove, 2012]

Patent Disclosure Practices

We interviewed nearly one dozen practitioners regarding their organizations' attitudes and perspective about the disclosure of intellectual property to standards. These included lawyers and business development executives at companies specializing in software and telecommunications, SSO executives, and academic technology transfer officials. The attitudes of the organizations towards disclosures of intellectual property varied dramatically. On the one hand, many organizations prefer to undertake generic disclosures, particularly

practices. (2) The definition of terms; classification of components; delineation of procedures; specification of dimensions, materials, performance, designs, or operations; measurement of quality and quantity in describing materials, processes, products, systems, services, or practices; test methods and sampling procedures; or descriptions of fit and measurements of size or strength. (reference here) if they are not seeking to license standard essential patents, but instead to make money off downstream products. One of the main reasons for undertaking generic disclosures was search cost containment: making a generic disclosure avoids the need for a patent search. This is especially true for firms with large patent portfolios. These firms found the process of sifting through patents to identify intellectual property relevant to a standard to be an ardouous and expensive task, which can consume thousands of hours of patent attorney time. The social dynamics of standard-setting process also impacts these decisions: even if the SSOs say that the participating firms do not need to engage in a patent search, there is often informal pressure to do so from other participants.

Since standards and patent applications evolve—sometimes rapidly—time also plays a major role. An initial disclosure may not be relevant if the standard changes considerably during the formulation process. Similarly, patents may add or lose claims as they move through the patent office, and may have a different scope as issued by various national patent offices. There is often a fear of being exposed from antitrust claims, regardless of what approach to patent disclosure the firm takes. If the firm does not disclose relevant IP, it could face antitrust claims, as seen in the litigation around Rambus and the JEDEC SSO. On the other hand, if the firm is perceived to over-disclose, there can also be accusations of preemptively discouraging competition. Over-disclosing can have other deleterious effects for the standard: higher licensing fees and a greater complexity and development cost immediately come to mind. For instance, to contain over-disclosures, the European Commission recommends that firms scrub lists of disclosed patents at the end of the standard-setting process, and include standard-relevant patents only.

The disclosure obligation is seen by firms to be very broad: often, the requirement by SSOs is that firms must disclose everything that is "likely to be relevant." In telecommunications, many SSOs have adopted the ETSI criterion that patents be disclosed when deemed "potentially essential." Licensing obligations are often considerably narrower than disclosure obligation. As a result of these requirements and the Rambus litigation, firms tend to feel they need to disclose a considerable number of patents: far more than will ever be included in any patent pool that will eventually form. Again, this concern pushes firms to lean towards generic disclosures.

Other firms prefer specific disclosures. Companies which are expecting to undertake licensing programs of SEPs are very careful and chart how different patents map to different standard functionalities. Thus, they are much more likely to have a good sense of which patents are relevant to a standardization effort. This observation has two results: first, the costs of generating the information needed for a disclosure are consequentially lower in these cases. Second, firms are disproportionately likely to make specific disclosures of their most important patents. In addition, the nature of the commitment to license with specific disclosures is more limited. In particular, with a specific disclosure, in many cases, the firm's commitment to license only covers the listed patents. Generic disclosure ensures that all relevant patents will be made available on FRAND terms.

However, specific disclosures help the firm with litigation and licensing negotiations if one is seeking to monetize SEPs. Even the presence or absence of an SSO disclosure is not explicitly a criterion used in judicial decisions in patent infringement cases, and the fact that the firm has undertaken such disclosure looks more favorable in court, particularly in a jury trial.

Of course, these decisions regarding disclosure may be affected by the rules of the SSOs themselves. In some cases, like IEC, specific disclosures are strongly encouraged. Some standard-setting bodies and consortia operate under the ground rules that all relevant patents will be available under FRAND terms—or royalty-free ones—unless clearly indicated. Thus, firms must explicitly identify which patents are not covered by these rules, and in some cases, must explain how these patents are relevant to the standard (normally, there is not a requirement for such an explanation).

Other relevant observations emerged in the interviews. Several observers suggested that firms that are active in "downstream" markets submit lower-quality material to SSOs. In particular, because other participants are eager to lock in their adoption of the standard, these "downstream" firms felt that their contributions were welcomed, even when not on par with the quality of the others. Another notable observation indicates that while large downstream firms are frequently eager to participate in SSOs, they are often unenthusiastic about the formation of an associated pool. They worry that such efforts may attract numerous smaller players that otherwise would not be able to collect license fees, either because the patents are not really essential or valid (due to the limited reviews conducted by patent pooling administrators), or else because the small firms would not be able to mount effective licensing campaigns. Many of our interviewees underlined that there is a strong firm heterogeneity in the level of interest and participation in SSOs and standard setting process, implying that there are many relevant patents never disclosed to SSOs.

2.2.2 Hypotheses

Large, practicing entites with significant downstream presence are more likely to participate in standard-setting process, as they are more eager not to jeopardize standard's completeness. For these entities, the downside of potentially low royalties is offset by the upside of rapid technology diffusion, favorable to the firm's downstream operations. In addition, as confirmed in our interviews, large search costs often prohibit these entities from making specific disclosures. This logic leads us to our first hypothesis:

H1: Conditional on participating in standard-setting efforts, large downstream firms are more likely to make a generic disclosure.

Because specific disclosures are much more costly to make, especially for firms with large portfolios, they will be made only when it is necessary to do so. In addition to search costs stemming from expensive and time-consuming patent-portfolio examinations, significant coordination costs are also present. If firms are looking to monetize SEPs, there must exist close coordination between engineers and scientists participating in SSOs and intellectual property strategists deciding on patent disclosures. When it comes to active patent monetization, limited specific disclosures look much more favorable in court if the owner is seeking to monetize these SEPs through licensing and litigation. Given that active patent monetization may lead to legal battles, as we've seen in *Microsoft Corp. v. Motorola Inc.*

for example, disclosed SEPs may be challenged in court. Hence, it is even more salient for these patents to read closely on the standard and be of high quality. This line of reasoning leads us to our second hypothesis:

H2: Conditional on being disclosed to SSOs, higher quality patents are more likely to be disclosed in a specific disclosure.

2.3 Empirical Analysis

2.3.1 Data Sources

Our analysis is based on a set of patent disclosures made through 2013 to seven large, modern SSOs:

1. *The American National Standards Institute (ANSI)*, an SSO overseeing the development of voluntary consensus standards for products, services, processes, systems, and personnel in the United States covering the wide range of industries. These include acoustical devices, construction equipment, dairy and livestock production, energy distribution, and many more. ANSI also coordinates United States standards with international standards and serves as official representative of United States to the two major international standards organizations, the International Organization for Standardization (ISO), and the International Electrotechnical Commission (IEC).

2. *The Advanced Television Systems Committee (ATSC)*, an SSO responsible for development of voluntary standards for digital television. The ATSC member organizations represent the broadcast, broadcast equipment, motion picture, consumer electronics, computer, cable, satellite, and semiconductor industries. The ATSC is working to coordinate television standards among different communications media focusing on digital television, interactive systems, and broadband multimedia communications.

3. *The European Telecommunications Standards Institute (ETSI)*, an SSO operating primarily in the telecommunications industry, and covering both equipment makers and network

providers. ETSI is responsible for standardization of Information and Communication Technologies (ICT) within Europe. These technologies include telecommunications, broadcasting and related areas such as intelligent transportation and medical electronics.

4. *The International Electrotechnical Comission (IEC)*, an SSO that creates and publishes international standards for all electrical, electronic and related technologies: anything from electromagnetics, electrical power and home appliances to semiconductors, fiber optics and nanotechnology.

5. *The Institute of Electrical and Electronics Engineers (IEEE)*, an SSO focused on developing global standards in a wide range of industries covering power and energy, biomedical, IT, telecommunications, transportation, nanotechnology and many more. Standards are developed by IEEE Standards Association (IEEE SA), a separate, community endorsed SSO within IEEE.

6. *The International Organization for Standardization (ISO)*, the world's largest developer of voluntary international standards covering a large variety of technologies and industries: from food safety and computers to energy, agriculture and healthcare.

7. *The International Telecommunication Union (ITU)*, a specialized agency of United Nations responsible for information and communication technologies. ITU allocates global radio spectrum and satellite orbits, develops the technical standards that ensure interconnection of networks and technologies in the global information and communication technology sector.

Our analysis starts with an identification of all standards developed by these seven SSOs. For every standard in our sample, we then identify all specifically disclosed US patents and patent owners, as well as all entities making generic patent disclosures.[10]

[10]While there are many international patents in our sample of disclosed patents, our analysis focuses on the US patents mainly because of the large size of downstream US markets and the "duty of candor" – a duty to disclose to USPTO all information material to patentability, or potentially deem the patent unenforcable. The

This proces results in a dateset covering 1,589 standards. This comprises 7,475 specific patent-standard disclosures belonging to 313 different entities and 2,883 generic declaration letters covering 134,800 standard-eligible patents belonging to 353 different entities. Table 2.1 shows the overall numbers of disclosed patents and standards by disclosure type covered in our dataset.

Table 2.2 summarizes numbers of disclosed patents by disclosure type and SSO.

Since generic declaration letters do not list any specific patents, but rather provide a general statement of "we believe that we have patents relevant to the implementation of standard X" type, there is a need to identify all patents that could *potentially* be disclosed via such statement. To acomplish this, we first build patent portfolios for all 353 entities making generic disclosures to standards in our sample. Assembling patent portfolios is a difficult task. Numerous variants of patent-seeking institution names appear in USPTO records. These are caused by either the variation in patent-prosecuting law firms or by human error and incorrectly spelled names. In addition, subsidiary and parent companies often appear as patent assignees completely independent of one another. For example, we could have patent A assigned to Philips North America, patent B assigned to Philips Healthcare, and patent C assigned to Philips Corporation. Since Philips North America and Philips Healthcare are both subsidiaries of Philips Corporation, all three patents should be grouped together as a part of Philips Corporation patent portfolio.[11] We use a set of special features available in Thomson Innovation database to aggregate patent portfolios more accurately than the raw USPTO patent records would allow us to do. We use the browse feature in Thomson Innovation Assignee/Applicant search field to identify all possible assignee name variations. This feature is used together with a unique 4-letter Assignee Codes available

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large size of the downstream US markets leads us to believe that our results closely mirror the results one would find if the international patents were to be included. In addition, the USPTO "duty of candor" requirement is one of the most stringent, without its equivalent counterpart in other parts of the world like Europe, for example. As a consenquence, all citation-based patent quality measures calculated over the set of the US patents should be more representative of the true patent quality than if calculated over the set of international patents.

[11] NBER patent dataset corrects this problem, but since it does not cover US patents issued after 2006, we cannot use it [Hall et al., 2002].

Table 2.1: *Summary of Patent Disclosures*

Disclosure Type	*Standards*	*Declarations**	*Patent-specific Disclosures†*	*US Patents Disclosed‡*	*US Patents Disclosed - Pool Related§*	*Count of Pooled Patents*	*Entities Represented*	*Manufacturers§§*
Generic	1,082	2,498	-	285,972	134,800	290	353	174
Specific	1,589	2,883	27,013	7,475	2,937	242	313	163

* When specific disclosures are made, we count only those declaration letters disclosing US patents and/or patent applications

† Number of unique disclosed patent-standard pairs

‡ Number of unique US patents disclosed

§ Number of unique US patents disclosed to patent-pool related standards

§§ Entities with primary SIC code between 2000 and 3999

Table 2.2: *Summary of Patent Disclosures by SSO*

Disclosure Type	*SSO*	*Declarations**	*Patent-specific Disclosures†*	*US Patents Disclosed‡*	*US Patents Disclosed - Pool Related§*	*Count of Pooled Patents*	*Entities Represented*	*Manufacturers§§*
	ANSI	542	-	137,548	397	62	94	55
	ATSC	36	-	45,979	40,917	24	24	14
	ETSI	501	-	31,525	12,573	27	23	11
Generic	*IEC*	420	-	192,974	53,816	265	139	77
	IEEE	671	-	181,723	23,478	97	160	79
	ISO	313	-	121,910	74,692	61	75	38
	ITU	15	-	2,338	1,497	9	4	3
	ANSI	150	449	263	0	1	74	42
	ATSC	22	432	409	351	95	18	11
	ETSI	1,216	23,661	5,711	2,326	109	94	46
Specific	*IEC*	721	465	294	127	16	63	37
	IEEE	259	921	634	41	19	101	57
	ISO	220	475	275	109	16	67	39
	ITU	295	610	351	98	10	78	40

* When specific disclosures are made, we count only those declaration letters disclosing US patents and/or patent applications

† Number of unique disclosed patent-standard pairs

‡ Number of unique US patents disclosed

§ Number of unique US patents disclosed to patent-pool related standards

§§ Entities with primary SIC code between 2000 and 3999 in Thomson Innovation to identify one of approximately 22,300 patenting organizations worldwide and map them to all subsidiaries listed in Thomson database. This enables us to count and aggregate US patents and patent applications wherever a firm or its subsidiary appears as an assignee or applicant on the patent record. Using this approach, we are able to identify almost 300,000 patents. Since we want to limit our patent sample only to those patents relevant to standards in question, we use patent International Patent Classification (IPC) technology codes to accomplish this. First we use specifically disclosed patents to build libraries of IPC codes associated to every standard with specifically disclosed patents. Next we compare these libraries with IPC codes assigned to generically disclosed patent portfolios. All generically disclosed patents having one or more IPC codes equal to one or more standard-relevant IPC codes are deemed as standard-eligible. All other patents are dropped. This process yields 134,800 standard-eligible patents.

We obtain additional information about firms disclosing the patents to SSOs from the Standard & Poor's Capital IQ and Compustat databases. These databases integrate financial and operational information on thousands of companies worldwide. We use Capital IQ's name-matching feature to match patent owner names to standardized entity names. We then assign a unique identifier to each entity in our sample and to map it to the parent company. Similarly to what we do with patents, we also aggregate all patent disclosures on a parent company level. Mergers and acquistions, as well as company name changes are tracked over time, and mapped to the patent disclosure date to ensure the most accurate mapping. For example, if we have separate disclosures from Philips North America and Philips Healthcare, we map both of these companies to their ultimate parent—Philips Corporation. We use Capital IQ to obtain time series data on firm size, revenue and earnings, R&D spending, capital expenditures, primary industry, age, and subsidiary-parent relationships. Since firms change their activities and industries over time, we also use S&P Compustat to get historical firm segment information encompassing product and geographical industry segment data.

2.3.2 Disclosure Preferences Across the Value Chain

Variables

To test if the large, downstream firms are more likely to use generic disclosures, we first need to agnostically determine if firms who disclose patents to standards have downstream presence relative to those standards. For example, if a firm makes a patent disclosure to 3G wireless standard, while it contemporaneously manufactures 3G based products like cellular phones, then that firm is downstream relative to 3G standard. This requires us to make a link between industry segments, technical standards and firm activities. To link standards with relevant industries, we use all specifically disclosed patents to create a list of standard-relevant IPC codes, and link those to NAICS industry codes. Past studies have generally linked patent classes to relevant industries by using one of the two publically available patent-to-industry concordances. The first one is Yale Technology Concordance (YTC), originally developed by Evenson et al. [1991], and the second one is Brian Silverman's Technology Concordance described in Silverman [1999]. Both of these concordances are probabilistic links of patent technology classes to industry codes based on a set of Canadian patents which were assigned industry codes in the early 1990s. Unfortunately, because these concordances are based on 1990s industry codes, some of the important new industries—like wireless communications—are largelly absent. To get around this problem, we use a newly developed patent-industry concordance known as Algorithmic Links with Probabilities (ALP) approach [Lybbert and Zolas, 2014]. This approach exploits recent advances in text analysis and relies on a keyword extraction from the patents themselves and subsequent probabilistic matching to textual descriptions of technology, industry or trade classifications. To generate the concordance, Lybbert and Zolas [2014] use the full PATSTAT database from the European Patent Office (EPO), and arrive at two-way probability distributions of 1) the IPC technology classes used within each industry and 2) industries using certain types of IPC technology classes.[12]

[12]Lybbert and Zolas [2014] concordance is available from the World Intellectual Property Organization (WIPO) at: http://www.wipo.int/export/sites/www/econ_stat/en/economics/zip/wp14_concordance.zip

Before we apply ALP concordance, we create lists of all 4-digit IPC technology codes relevant to each individual standard by using specifically disclosed patents. We then match those IPC codes to NAICS codes obtained from ALP concordance dataset.[13] Once we generate a map of NAICS codes for each standard, we resort to S&P Compustat Historical Segment data for each firm making a disclosure. Historical segment NAICS codes are compared to lists of standard-relevant NAICS codes, and those firms whose historical NAICS codes match any of standard-relevant NAICS codes are labelled as *downstream* to that particular standard. For example, if firms 1 and 2 disclose patents to some standard A, and ALP concordance results in that standard A being associated with NAICS codes X and Y, then if firm 1's historical NAICS code is X at the time of its disclosure, and firm 2's historical NAICS code is Z at the time of its disclosure, firm 1 will be labelled as *downstream* and firm 2 will be labelled as *upstream*. In addition, since they are not listed in Compustat, we manually classify all universities and research institutes as upstream entities.

Counting disclosures can also be tricky. For example, a single specific declaration letter can disclose multiple patents to multiple standards, while a generic declaration can disclose potentially many patents to one or more standards. To compare disclosure preferences, we disregard all patents and observe disclosure letters submitted by a firm in a given year only. So, even if firm 1 was to disclose 10 patents to standard A in 5 different disclosures during the course of one year, we would count this as a single specific disclosure made by firm 1 to standard A in that year. To reduce sample variability and ensure consistent comparison across firms, we analyze only those standards receiving both specific and generic disclosures. Standards receiving only specific or only generic disclosures are dropped from the sample. This results in a final sample of 840 disclosures.

Since our hypothesis contends that the size of downstream firms will increase the likelihood of these firms to utilize generic disclosures, we need to account for firm size

[last accessed: 06/10/2015].

[13]While we generate frequency weights for IPC-standard lists, we do not use them in the final analysis as to not overcomplicate the process. Rather, we us a simple discrete measure of "match" or "no-match".

in the analysis. Unfortunately, firm size is not a directly measurable quantity, so we are forced use a set of financial and operational proxies. These include total revenue, R&D expenditures, property, plant and equipment, number of employees and capital expenditures. For each one of these proxy variables, we calculate the logarithm of the average over a 3-year window (from the year of disclosure to two years prior).[14] Table 2.3 provides more detailed descriptions of variables used in this part of the analysis.

Summary statistics are reported in Table 2.4.

Specification

To test if large, downstream firms are more likely to use generic disclosures, we use a logistic specification:

$$Pr(Spec_{i,s,t} = 1) = F(\alpha + \beta \times D_{i,s,t} + \gamma \times S_{i,t} + \delta \times D_{i,s,t} \times S_{i,t} + Ind_i + Year_t + SSO_s + \epsilon_{i,s,t})$$

where

$$F(z) = \frac{e^z}{(1 + e^z)}$$

In this specification, the dependent variable $Spec_{i,s,t}$ is a dummy equal to 1 if a specific disclosure was made by the firm i to a standard s in a year t. $D_{i,s,t}$ is a dummy equal to 1 if the firm i was determined to be *downstream* to a standard s in a year t. $S_{i,t}$is a size proxy for the firm i in a year t. Ind_i is industry sector fixed effect (4-digit SIC level), $Year_m$ is a year fixed effect and SSO_s is SSO fixed effect. We are particularly interested in the sign of δ coefficient on the interaction term of the downstream dummy and firm size proxy. Negative δ would indicate that size makes downstream firms less likely to make specific disclosures.

Given that firm size proxies are highly correlated, we test our specification on each proxy independently. Correlation coefficients for firm size proxies range between 0.77 and 0.95 as shown in Table 2.5.

[14]Our results are robust to changes in time-window length.

Table 2.3: *Disclosure Preference Analysis – Variable Descriptions*

Variable	***Description***
Specific Disclosure	Dummy equal to 1 if a disclosure was specific; 0 otherwise
Downstream	Dummy equal to 1 if the firm was determined to have downstream presence
Year	Year in which the disclosure was made
Firm Age	Age of the firm (in years) at the time the disclosure was made
Total Revenue (3 year Average)	Mean ***Total Revenue*** in a 3-yr time window before the disclosure
R&D Expenses (3 year Average)	Mean ***R&D expenditures*** in a 3-yr time window before the disclosure. ***R&D Expenditures*** are any expenses linked to the R&D of a company's goods or services. R&D expenses are operating expenses that are incurred in the process of finding and creating new products or services.
Property, Plant and Equipment (3 year Average)	Mean ***Property, Plant and Equipment*** balance in a 3-yr time window before the disclosure. The ***Property, Plant and Equipment*** is a balance sheet item that represents a summation of all company's purchases of physical assets (like land, buildings, and equipment) *deployed* in the productive operation of the business, less any amortization.
Number of Employees (3 year Average)	Mean ***Number of Employees*** in a 3-yr time window before the disclosure. Serves as a proxy for firm size. Can also be used to normalize financial measures like revenue, R&D spending, etc.
Capital Expenditures (3 year Average)	Mean ***Capital Expenditures*** in a 3-yr time window before the disclosure. These are monies used by a company to acquire or upgrade physical assets such as property, industrial buildings or equipment. These investments are usually made by firms to maintain or increase the scope of their operations.

Table 2.4: *Disclosure Preference Analysis – Summary Statistics*

Variables	N	mean	sd	min	max
Firm Has Downstream Presence	840	0.731	0.444	0	1
Specific Disclosure	840	0.363	0.481	0	1
Total Revenues (Logged 3-year Average)	826	10.14	3.018	0.0497	18.84
R&D Expenditures (Logged 3-year Average)	716	7.527	2.327	-0.651	14.62
Property, Plant, and Equipment (Logged 3-year Average)	815	8.484	3.311	-2.419	17.88
EBITDA (Logged 3-year Average)	775	8.478	2.961	-2.553	17.03
Total Employees (Logged 3-year Average)	701	10.60	2.007	4.034	13.43
Capital Expenditures (Logged 3-year Average)	821	7.231	3.172	-3.310	16.76
Year Disclosed	840	2003	5.598	1986	2013

Table 2.5: *Correlation Matrix for Firm Size Measures*

Total Revenues (Logged 3-year Average)	1.000					
R&D Expenditures (Logged 3-year Average)	0.944	1.000				
Property, Plant, and Equipment (Logged 3-year Average)	0.950	0.894	1.000			
EBITDA (Logged 3-year Average)	0.942	0.894	0.915	1.000		
Total Employees (Logged 3-year Average)	0.858	0.774	0.867	0.831	1.000	
Capital Expenditures (Logged 3-year Average)	0.950	0.907	0.987	0.930	0.843	1.000

Results

Our results are reported in Table 2.6.

We find negative effects of firm size on the likelihood of specific disclosure, which suports H1. While the downstream presence by itself increases the probability of specific disclosures, the firm size does not. The coefficient on the *Downstream* dummy is positive and significant for all of the firm-size proxy regressions, implying that downstream firms alone would be more likely to make specific disclosures. However, the sign on the interaction coefficient of every *Firm Size* proxy with the *Downstream* dummy is negative and significant, indicating that an increase in firm size leads to a decrease in likelihood of specific disclosure for downstream firms. of size and downstream presence is negative across the board. We control for time, SSO and industry (4-digit SIC) fixed effects, and report robust standard errors. For robustness, we also run OLS models with fixed-effects, but the results do not change.

2.3.3 Disclosure Preferences and Patent Value

Variables

Next, we test whether higher quality patents are more likely to be disclosed in specific disclosures, and to reduce sample variability, we first match patents from specific disclosures to standard-eligible patents from generic disclosures. For all specific disclosures, we create a standard-IPC code map using disclosed patents' 6-letter IPC codes. Next, we match these

Table 2.6: *Disclosure Type Results – Dependent Variable is* Specific Disclosure

	Downstream	Total Revenues					R&D Expenditures				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
VARIABLES											
Firm Has Downstream Presence	-0 180	-0 221	1 611***	1 420**	1 585**	1 400*	-0 207	1 786***	1 592**	1 699**	2 110***
	(0 160)	(0 166)	(0 594)	(0 655)	(0 699)	(0 744)	(0 195)	(0 616)	(0 663)	(0 696)	(0 808)
Total Revenues (Logged 3-year Average)		-0 0912***	0 0280	0 0600	0 0731	0 00386					
		(0 0263)	(0 0440)	(0 0517)	(0 0551)	(0 0602)					
Downstream Presence x Total Revenues			-0 181***	-0 160***	-0 179***	-0 130*					
			(0 0568)	(0 0611)	(0 0647)	(0 0680)					
R&D Expenditures (Logged 3-year Average)							-0 206***	-0 0159	0 0145	0 0313	0 0763
							(0 0379)	(0 0663)	(0 0730)	(0 0761)	(0 0867)
Downstream Presence x R&D Expenditures								-0 274***	-0 245***	-0 264***	-0 292***
								(0 0809)	(0 0862)	(0 0901)	(0 101)
Capital Expenditures (Logged 3-year Average)											
Downstream Presence x Capital Expenditures											
Property, Plant, and Equipment (Logged 3-year Averag											
Downstream Presence x Property, Plant, and Equipmen											
EBITDA (Logged 3-year Average)											
Downstream Presence x EBITDA											
Firm Age (Logged)											
Downstream Presence x Firm Age											
Number of Employees (Logged 3-year Average)											
Downstream Presence x Number of Employees											
Constant	-0 431***	0 503*	-0 723	-0 229	0 343	1 408	1 116***	-0 268	-0 971	-0 504	-0 0476
	(0 136)	(0 298)	(0 479)	(1 844)	(1 896)	(1 409)	(0 321)	(0 511)	(0 801)	(0 908)	(1 179)
Year Fixed Effect	No	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes
SSO Fixed Effect	No	No	No	No	Yes	Yes	No	No	No	Yes	Yes
Industry Fixed Effect (4-digit SIC)	No	No	No	No	No	Yes	No	No	No	No	Yes
Observations	840	826	826	814	814	808	716	716	708	708	692
Log-Likelihood	-549 7	-532 5	-526 6	-477 8	-466 7	-433 4	-450 1	-444	-403 4	-394 3	-354 5
Pseudo R-squared	0 00114	0 0141	0 0249	0 106	0 127	0 183	0 0394	0 0525	0 132	0 152	0 224

	Capital Expenditures					EBITDA				
	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
VARIABLES										
Firm Has Downstream Presence	-0 273	1 211***	1 050**	1 185**	1 018*	-0 324*	1 976***	2 106***	2 390***	2 097***
	(0 169)	(0 426)	(0 466)	(0 494)	(0 551)	(0 176)	(0 560)	(0 630)	(0 655)	(0 672)
Capital Expenditures (Logged 3-year Average)	-0 0989***	0 0269	0 0526	0 0657	-0 0156					
	(0 0259)	(0 0398)	(0 0461)	(0 0489)	(0 0572)					
Downstream Presence x Capital Expenditures		-0 205***	-0 177***	-0 199***	-0 131*					
		(0 0551)	(0 0581)	(0 0610)	(0 0668)					
EBITDA (Logged 3-year Average)						-0 111***	0 0711	0 125**	0 146**	0 0438
						(0 0286)	(0 0488)	(0 0562)	(0 0591)	(0 0684)
Downstream Presence x EBITDA							-0 263***	-0 268***	-0 304***	-0 226***
							(0 0619)	(0 0678)	(0 0706)	(0 0752)
Constant	0 322	-0 632*	-1 480**	-0 903	-0 00797	0 528*	-1 136**	-3 649***	-3 552***	-2 342*
	(0 238)	(0 337)	(0 745)	(0 869)	(0 876)	(0 294)	(0 474)	(1 167)	(1 288)	(1 352)
Year Fixed Effect	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes
SSO Fixed Effect	No	No	No	Yes	Yes	No	No	No	Yes	Yes
Industry Fixed Effect (4-digit SIC)	No	No	No	No	Yes	No	No	No	No	Yes
Observations	821	821	808	808	802	775	775	762	762	759
Log-Likelihood	-526 5	-518 1	-471 4	-459 9	-428 7	-490 6	-480 7	-431 1	-421 4	-396
Pseudo R-squared	0 0180	0 0336	0 111	0 133	0 185	0 0194	0 0392	0 129	0 148	0 197

	Number of Employees				
	(22)	(23)	(24)	(25)	(26)
VARIABLES					
Firm Has Downstream Presence	-0 255	3 622***	2 866**	3 324***	2 508*
	(0 179)	(1 013)	(1 151)	(1 259)	(1 398)
Number of Employees (Logged 3-year Average)	-0 117***	0 127*	0 179**	0 220**	0 186
	(0 0393)	(0 0771)	(0 0882)	(0 0985)	(0 126)
Downstream Presence x Number of Employees		-0 358***	-0 286***	-0 327***	-0 232*
		(0 0908)	(0 103)	(0 111)	(0 129)
Constant	0 900**	-1 804**	-3 859***	-3 689**	-2 854*
	(0 455)	(0 881)	(1 341)	(1 480)	(1 712)
Year Fixed Effect	No	No	Yes	Yes	Yes
SSO Fixed Effect	No	No	No	Yes	Yes
Industry Fixed Effect (4-digit SIC)	No	No	No	No	Yes
Observations	701	701	693	693	682
Log-Likelihood	-458 3	-449 6	-407 3	-397	-365 2
Pseudo R-squared	0 0108	0 0295	0 114	0 136	0 189

Robust standard errors in parentheses
*** p<0 01, ** p<0 05, * p<0 1

standard-IPC code pairs from specific disclosures to standard-IPC code-patent pairs from generic disclosures, and drop all observations that do no match. This procedure effectively keeps only those standards present in both specific and generic disclosure datasets, and within those standards only those generically disclosed patents which have at least one 6-letter IPC code corresponding to their specifically disclosed counterparts. Our final sample contains 108,019 generic and 7,475 specific patents. Summary statistics are given in Table 2.7.

Table 2.7: *Patent Quality Analysis – Summary Statistics*

Variables	N	mean	sd	min	max
Specific Disclosure	63765	0.08233	0.27487	0	1
Forward Citations (Truncated)	63765	1.22786	1.62564	0	46.24749
Patent Scope	63765	1.58625	0.91639	1	12
Number of Claims	63750	19.13075	13.83417	1	269
Patent Originality	63765	0.50233	0.25746	0	0.94690
Number of Patent References	63765	14.71550	28.41547	1	841
Number of Non-Patent Refences	63765	3.42933	11.47524	0	455
INPADOC Family Size	63765	4.67264	19.55966	1	934

To measure economic value of these patents, their technological importance and subsequent technological impact, we use a set of literature-based patent quality indicators:

1. *Patent Scope* measures the technological breadth of patents by accounting for the number of International Patent Classification (IPC) technology classes each patent is assigned to. Patent scope was shown to have a significant impact on firm valuation: broader patent scope translates to higher firm valuation [Lerner, 1994]. For a patent i, the patent scope is calculated as:

$$Scope_i = (Number\ of\ 4 - digit\ IPC\ codes)_i$$

2. *Patent Family Size* is an indicator of economic value of patent rights. The size of the

patent family is highly correlated to the patent "lifetime", i.e. the time from the initial patent application to patent expiration or assignee's decision not to renew the patent [Putnam, 1996, Lanjouw et al., 1998]. In addition, large patent families have been shown to be more valuable [Harhoff et al., 2003]. Patent family size is measured as the number of different patent jurisdictions (nations) in which patent protection was sought, excluding European and World patents.[15]

3. *Number of Claims* determine the boundary of technology exclusion rights described in the patent and are associated with technological and economic value of inventions [Lanjouw and Schankerman, 2001, 2004].

4. *Number of Patent References (Backward Citations)* was shown to be postively correlated with the patent value [Harhoff et al., 2003]. The number of patent references is the number of other patent documents (including patent applications and self-citations) cited in the patent.

5. *Number of Non-Patent References (Backward Citations)* is correlated with more significant knowledge content [Cassiman et al., 2008].The number of non-patent references such as scientific journals and books is also associated with higher patent quality and approval rates [Branstetter and Ogura, 2005].

6. *Number of Forward Citations* is associated with the technological importance and overall patent quality [Trajtenberg, 1990]. The number of forward citations is the number of times a patent document is cited in subsequent patents. We correct all forward citation counts for truncation on a 3-digit US patent class and cohort-year basis [Hall et al., 2002].

7. *Patent Originality* measures the technological breadth of patent references. Low originality score implies that a patent's backward citation set is technologically narrow

[15] European and World patents do not give patent protection in individual countries. An applicant still needs to request a patent to be granted and comply with national laws in order to gain protection. If so, then a national patent is issued and end-point protection is obtained.

(a small and focused number of technology classes), while the high originality score implies that backward citations belong to a larger and much broader set of technology classes [Trajtenberg et al., 1997, Hall and Trajtenberg, 2004]. The measure of patent originality is calculated using 4-digit IPC classes for all identified backward patent citations as:

$$Originality_i = 1 - \sum_{j}^{N_i} OS_{ij}^2$$

where OS_{ij}^2 is a share of citations cited by a patent i that come from a patent class j out of set of N_i patent classes belonging to a set of all identified patent references cited by patent i. *Originality* is calculated using all the references retrieved from Thomson Innovation database.

Specification

We use simple logistic regression to test if higher quality patents are more likely to be disclosed in specific disclosures:

$$Pr(Spec_{i,sso,t} = 1) = F(\alpha + \beta \times Patent_i + Year_t + SSO_{sso} + \epsilon_{i,s,t})$$

where

$$F(z) = \frac{e^z}{(1 + e^z)}$$

In this specification, the dependent variable $Spec_{i,sso,t}$ is a dummy equal to 1 if a patent i was disclosed in a specific disclosure to SSO sso in a year t. $Patent_i$ is the patent value measure. $Year_m$ is a year fixed effect and SSO_{sso} is SSO fixed effect. We are particularly interested in the sign of β coefficient on the patent value measure, and expect it to be positive.

In this particular case, we aggregate disclosures on SSO level for two reasons. First, our interviewees have indicated SSO-specific disclosure policies to be a major driver of how and what firms disclose. Second, because multiple patents are disclosed to many standards within and across SSOs, aggregating disclosures on the standard level would lead to many duplicate observations, and it would not be entirely appropriate to control for standard-level fixed effects. Since there are still many patents disclosed to multiple standards within SSOs, to make sure we're not overstating the significance of our results, we perform a simple degree-of-freedom correction and create a dummy for each year and SSO and average over them before running the regressions. This reduces the number of observations to 63,598.

Results

Table 2.8 reports the results.

We obtain positive and statistically significant effects of patent quality on the likelihood of those patents being specifically disclosed. This supports H2. The coefficients on the patent quality measures of scope, family size, number of claims, number of patent references, number of non-patent-literature references and originality are all positive and significant, implying that higher quality patents are indeed more likely to be disclosed to SSOs via specific disclosures. We control for time and SSO, and report robust standard errors. For robustness, we also run OLS models with fixed-effects, but the results do not change.

2.4 Conclusion

Our goal was to extend the quantitative empirical literature dealing with standard-setting and illuminate standard-essential patent disclosure mechanisms made during standardization process. In light of opportunities for abuse of standard-setting process, and large downstream economic impact such abuses may have, this issue is very important. Through the combination of economic theory and interviews with practicioners and regulators, we developed two hypotheses which we then tested using a novel dateset of all patent disclosures made to seven large SSOs. We were able to identify SEP owners who had downstream presence to relevant standards, and create a binary measure of downstream presence. While our measures of downstream presence can certainly be further refined, it is unclear if attempts to refine this measure with somewhat noisy proxies could aggravate errors-in-variables problem. In addition, we managed to create portfolios of standard-eligible patents using

Table 2.8: *Patent Quality Results – Dependent Variable is* Specific Disclosure

	Forward Citations (Truncated)			Patent Scope			Number of Claims		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES									
Forward Citations (Truncated)	0 00206	0 00351	0 0930***						
	(0 00995)	(0 0107)	(0 0142)						
Patent Scope				0 712***	0 737***	0 735***			
				(0 0138)	(0 0167)	(0 0203)			
Number of Claims							0 0148***	0 00891***	0 0137***
							(0 000899)	(0 00115)	(0 00121)
Year Fixed Effect	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
SSO Fixed Effect	No	No	Yes	No	No	Yes	No	No	Yes
Constant	-2 417***	-2 163***	2 769***	-3 742***	-3 625***	1 381***	-2 718***	-2 381***	2 565***
	(0 0190)	(0 138)	(0 270)	(0 0313)	(0 155)	(0 294)	(0 0241)	(0 142)	(0 274)
Observations	63,598	62,209	62,209	63,598	62,209	62,209	63,583	62,194	62,194
Log-Likelihood	-18045	-13268	-7914	-16430	-12017	-7203	-17909	-13229	-7889
Pseudo R-squared	1 50e-06	0 260	0 558	0 0895	0 330	0 598	0 00749	0 262	0 560

	Patent Originality			Patent References			Non-Patent References		
	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
VARIABLES									
Patent Originality	4 619***	4 403***	3 952***						
	(0 0919)	(0 107)	(0 132)						
Number of Patent References				0 0111***	0 0103***	0 00882***			
				(0 000582)	(0 000631)	(0 000649)			
Number of Non-Patent Refences							0 0188***	0 0185***	0 0172***
							(0 00138)	(0 00190)	(0 00192)
Year Fixed Effect	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
SSO Fixed Effect	No	No	Yes	No	No	Yes	No	No	Yes
Constant	-5 193***	-5 073***	-0 155	-2 616***	-2 326***	2 694***	-2 499***	-2 259***	2 783***
	(0 0633)	(0 162)	(0 321)	(0 0172)	(0 141)	(0 272)	(0 0154)	(0 141)	(0 270)
Observations	63,598	62,209	62,209	63,598	62,209	62,209	63,598	62,209	62,209
Log-Likelihood	-16262	-12063	-7339	-17573	-12938	-7817	-17819	-13119	-7856
Pseudo R-squared	0 0988	0 327	0 591	0 0262	0 278	0 564	0 0125	0 268	0 562

	INPADOC Family Size		
	(19)	(20)	(21)
VARIABLES			
INPADOC Family Size	0 00440***	0 00312***	0 00450**
	(0 000440)	(0 000466)	(0 000732
Year Fixed Effect	No	Yes	Yes
SSO Fixed Effect	No	No	Yes
Constant	-2 439***	-2 169***	2 868***
	(0 0145)	(0 136)	(0 270)
Observations	63,598	62,209	62,209
Log-Likelihood	-18005	-13253	-7932
Pseudo R-squared	0 00225	0 261	0 557

Robust standard errors in parentheses
*** p<0 01, ** p<0 05, * p<0 1

generic disclosures, and link them to patent quality measures.

Two hypotheses we developed are supported by our empirical results. We found strong support for our first contention that large, downstream firms are more likely to make generic disclosures to SSOs. The support for our second hypothesis that higher quality patents are more likely to be disclosed via specific disclosures was equally as strong.

Chapter 3

The Impact of Money on Science: Evidence from Unexpected NCAA Football Outcomes[1]

3.1 Introduction

Investments in science can generate large social returns. Scientific discoveries have eradicated diseases, reduced famine, increased labor productivity, and supported national defense. However, scientific laboratories and experiments are expensive to run and research funds are often the key limiting factor in scientific advancement. Together these facts make the level of R&D investment a central concern of university administrators and public policymakers. There is urgency about this issue in the United States where the federally-financed share of university research has fallen over the last forty years and recent recession-induced budget cuts have slashed states' investment in academic research. These developments prompted the America COMPETES Acts of 2007 and 2010 [National Research Council, 2012], which called for a doubling of funds to basic science, and a potential reauthorization of the Act in 2014. Despite its salience, the question of whether policymakers fund a socially-optimal

[1]Co-authored with Thomas Wollmann

level of R&D remains open, largely because there are few estimates of the causal impact of research expenditures on scientific discovery.

This paper estimates the dollar elasticity of research output across American universities. It addresses two empirical challenges. First, research grants tend to be awarded to more productive institutions. This endogeneity causes parameter estimates to be upward biased. Second, expenditure data that includes long-term projects of various lengths and lags will make tying money to outcomes difficult. For example, construction of the multi-billion dollar Large Hadron Collider began ten years prior to the first experiments. This errors-in-variables problem causes estimates to be downward biased. The first of these problems suggests—at a minimum—controlling for institution-specific effects, although this tends to amplify the bias from the second. To solve both problems, we exploit an exogenous shifter of marginal research funds between universities: the unexpected success of college football teams.

Identification relies on the fact that football team performance impacts cash flow to the university and, in turn, the funds available for research. Even if unobserved school-specific factors that drive research output also influence football team success, they are unlikely to influence *unanticipated within-season* changes to team success. We measure football team success using the Associated Press Top 25 Poll and use the difference between post-season and pre-season vote counts as the instrumental variable. Since the individual voting results of the Top 25 Poll are made public, and the professional sportswriters who vote have a significant reputational stake in properly forecasting teams' quality and teams' true prospects, the difference between post-season outcomes and pre-season expectations can be treated as random.[2]

Three aspects of this relationship aid greatly in obtaining results. The first is the degree to which swings in football fortunes impact overall school finances. Since the late 1980s college football has generated tens of billions in cash flow to American colleges and universities.

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[2]Readers unfamiliar with the context can consider an injury to a key player as the sort of random shock underlying this variation.

One of the more prominent examples is the University of Texas at Austin: in 2013 its football team generated more revenue than the majority of professional National Hockey League teams.[3]

At Louisiana State University, football revenue is nearly a third of total tuition receipts. A large portion of this revenue is ploughed back into the athletic department, but a sizable part is returned to the school's general account in the form of unrestricted funds. In addition, a successful football season on the field usually translates to a successful fundraising campaign off the field. For example, Texas A&M University raised more money the night after its star quarterback Johnny Manziel's Heisman Trophy win than it typically raises in a month, in turn setting records for quarterly and annual alumni giving.[4] The second is that this source of funds is highly volatile, which means that administrators are likely to treat these changes as temporary windfalls rather than opportunities to start long-term projects. The third is that much of a team's success is, in fact, quite unpredictable. This is empirically true in our data and a fact to which college football fans can attest.

We use a two-stage least squares (2SLS) specification to estimate the impact of money on scientific output, which we measure in four ways. When the output measures are scholarly articles and the citations that accrue to them, we estimate dollar elasticities of 0.31 and 0.59, respectively. When the output measures are new patent applications and the citations that accrue to them, we estimate dollar elasticities of 1.91 and 3.30, respectively. These estimates contrast sharply with non-IV estimates under the same specification, which tended toward zero. All calculations are made controlling for time and school effects and school-specific time trends. The non-IV results closely resemble prior work by Adams and Griliches [1996, 1998] and would lead to underinvestment in scientific research, with two important caveats as these results apply to policy-setting. First, since the predicted variation in research

[3]Smith, Chris. "College Football's Most Valuable Teams 2013: Texas Longhorns Can't Be Stopped." Forbes, December 18, 2013. http://www.forbes.com/sites/chrissmith/2013/12/18/college-footballs-most-valuable-teams-2013-texas-longhorns-cant-be-stopped (accessed December 2, 2014).

[4]Marty Holmes (Vice President, The Association of Former Students, Texas A&M University), telephone conversation with authors, July 2014.

expenditures is linear in the instrument, unexpected losses hurt research budgets as much as unexpected wins help them. The transfers of research funds between schools are assumed to be zero sum. Consequently, if the schools happen to be merely trading scarce output-producing assets—like highly productive scientists—then an aggregate increase in research expenditures might have no impact at all, even though our results predict a strong positive impact of expenditures on each *individual* institution. This seems unlikely, since small and perhaps temporary budget shocks are unlikely to result in long-term and expensive commitments like hiring. Moreover, these high output faculty would bring federal grants along with them, a point we address below and do not see in the data. Delineation of exact mechanisms that govern research-fund allocation processes within universities is beyond the scope of this paper. Nonetheless, this is an important question we leave for future research. Second, the main specification relies on a set of important assumptions about the timing of football success, research funding, and scientific publishing. Misspecification can bias the coefficients, so we provide support for our assumptions and discuss the factors underlying the temporal relationships.

Figures 3.1-3.2 illustrate the reduced-form relationship. The x-axis in each shows unanticipated football success, measured by within-season changes in Associated Press voting. In Figure 3.1, the y-axis in the top panel represents the log of the count of scholarly articles published and in the bottom panel represents the log of the count of the citations that accrue to those articles. In Figure 3.2, the y-axis in the top panel represents the log of the count of new patent applications and in the bottom panel represents the log of the count of the citations that accrue to those applications. We remove school and year fixed effects as well as school-specific time trends from the variables on both axes. The x-axis has been standardized across polls by standard deviation and lagged appropriately. The positive impact of unexpected football outcomes on all four measures of scientific discovery are positive (and significant at 95%).

We can strengthen the causal interpretation of this relationship with an exogeneity check. Since we observed research funding from federal and non-federal sources separately, we can

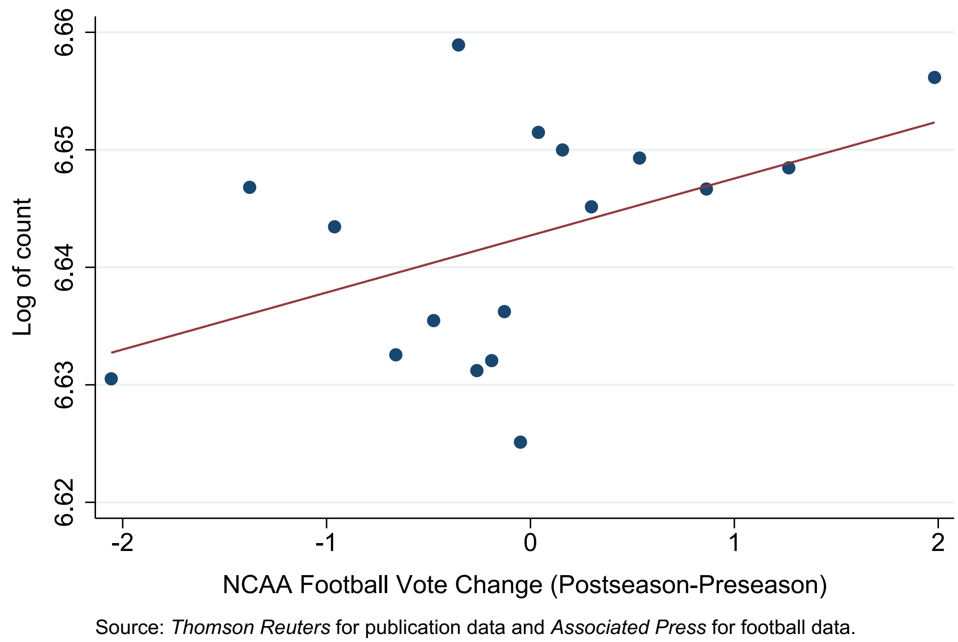
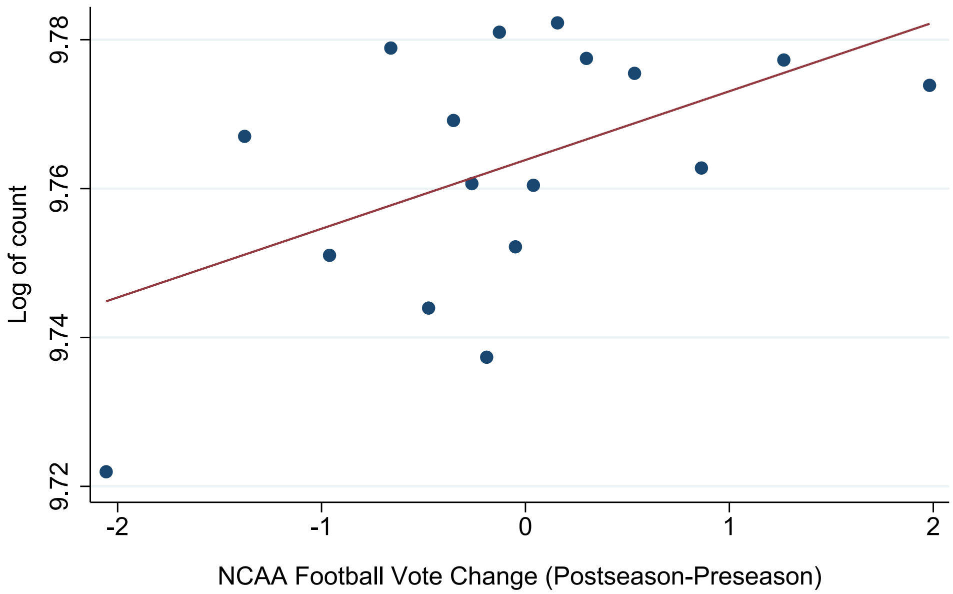


Figure 3.1: *Football and scholarly articles*

assess the impact of unexpected football outcomes on both independently. Of course while research funding coming from non-federal sources should be affected by football, those coming from federal sources should not. We find strong evidence for this fact in the data.

This paper contributes to several literatures. In measuring the elasticity of university research expenditures, it follows closely in the footsteps of Adams and Griliches [1996, 1998]. Their cross-sectional OLS specification combines observations over their panel and finds a dollar elasticity of 0.5 when the outcome measure is the number of scholarly articles and 0.6 when the outcome measure is the number of citations that accrue to them. However, when they include university fixed effects to control for institution-specific unobservables, elasticities fall by 80% and are no longer separate from zero. They conclude, *"To date we have little hold over changes in financial and other circumstances that bring about a change in the stream of a university's research output."* This is precisely the issue we wish to address.

The scope of our study extends beyond scientific publishing to patenting behavior. After the passage of the Bayh-Dole Act in 1980 allowed academic institutions to retain ownership of inventions developed through federally funded research, it incited a strong

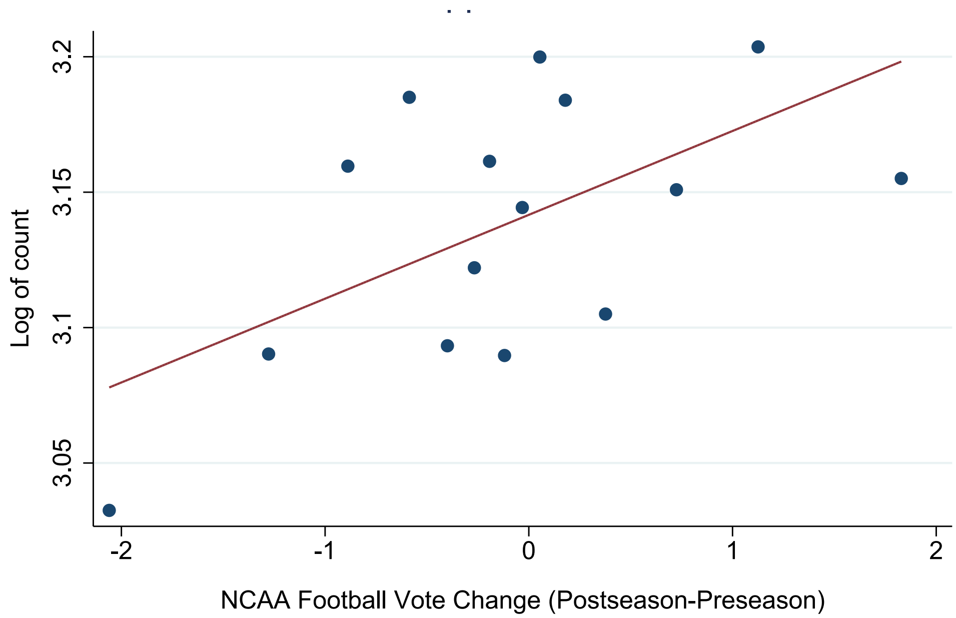


Source: *Thomson Reuters* for publication citation data and *Associated Press* for football data.

Figure 3.2: *Football and scholarly article citations*

growth in academic patenting and patent licensing [Henderson et al., 1998, Sampat et al., 2003, Hausman, 2013]. Pakes and Griliches [1980, 1984] were first to consider patents as an outcome of interest. They found a positive relationship with lagged investment and knowledge stocks in firms.[5] Relatedly, Azoulay et al. [2014] study the impact of government research grants on private sector pharmaceutical and biotech firms. They exploit institutional features of the granting institution to address endogeneity issues and find that a $10 million increase in government funding generates 3.3 additional patents. Jaffe [1989] spawned a related stream of papers that measured whether R&D efforts spillover to local private firms. The focus on spillovers, however, led this paper and those that followed to focus on exogenous shifts to university research activity rather than university research spending *per se*. As an example, Hausman [2013] uses the Bayh-Dole Act to credibly demonstrate these spillovers on a host of private-sector outcomes like profits and employment. In addition, we shed more light on the mechanisms utilized by academic institutions to fund

[5] See Griliches et al. [1988] for a survey of the early literature.

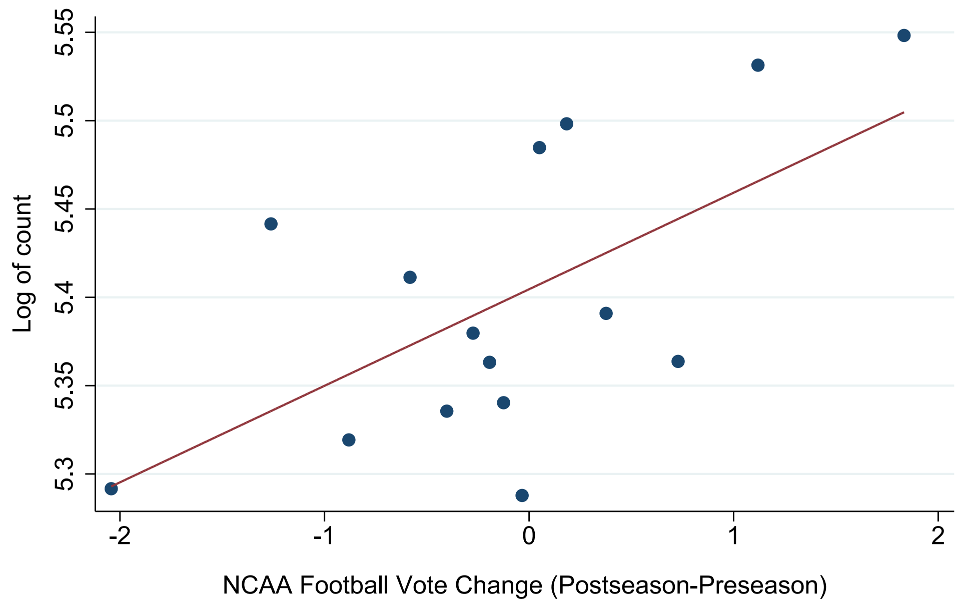


Source: *Thomson Reuters* for patent data and *Associated Press* for football data.

Figure 3.3: *Football and new patent applications*

scientific R&D. The roles of government [Nelson, 1959, Jaffe, 1989, Henderson et al., 1998] and private industry [Mowery and Rosenberg, 1989, Cohen et al., Wright et al., 2014] have been extensively studied, while the role of science philanthropy only recently started to attract more attention [Murray, 2013].

This paper also contributes to recent literature using athletic outcomes for identification. Card and Dahl [2011], for example, study how external cues precipitate violence by showing that domestic abuse rises in cities where the local NFL team suffers an unexpected loss. Anderson [2012] asks whether schools are justified in their large investments into college sports and uses the difference between realized outcomes and betting spreads to show that winning attracts students and donations. Meer [2013] tests habit formation in charitable giving by using prior years' athletic success as an instrument for past giving. The tie between athletics and donations was established previously in Meer and Rosen [2009] using university microdata.



Source: *Thomson Reuters* for patent data and *Associated Press* for football data.

Figure 3.4: *Football and patent citations*

3.2 US College and University Research

Spending Levels

Colleges and universities conduct more than 15% of total research and development in the United States, which totaled $450 billion in 2013. They also account for more than 50% of basic science expenditures [Battelle Memorial Institute]. These institutions historically relied heavily on the federal government for funding, although the federally-funded share of research has fallen from 78% to 67% over the past four decades. Private funding from corporations has stayed essentially flat, despite wide year-to-year variation. Institutionally-sourced funds have partially compensated, rising from 11% to almost 20% over the same period [National Science Foundation, 2013]. Survey data also suggests this increase is insufficient: 84% of US academic researchers expressed concern over the reduction in US federal R&D funding. For comparison, consider the following: despite the widely publicized shortage of qualified R&D staff in the United States, only 48% of researchers listed this issue as a concern [National Research Council, 2012].

Congress and the White House have taken notice and begun to act on these concerns. In 2005, Congress asked the National Research Council to prepare a plan that would ensure American competitiveness in science and technology. Congress then provided bipartisan support for the America COMPETES Act, which President Bush signed into law in 2007. The Act emphasizes investment in the science, technology, engineering, and mathematics fields and authorizes a doubling of National Science Foundation (NSF) grants for many fields by 2011. In 2009, Congress requested a follow-up report. Two years later, President Obama signed a reauthorization of the bill, the America COMPETES Act of 2010. The budget sequestration process of 2013 reignited this debate. Ultimately, the authorized funding increases were not realized. This has prompted the Director of the National Institute of Health to worry that "we will lose a generation of young scientists" and that "a lot of good science just won't be done."[6]

As of the time of writing, Congress has proposed but not yet passed another reauthorization of the Act. A central driver of this debate is uncertainty about where the funding level stands in relation to the optimal social level of R&D, which itself turns on the underlying return on research investment. Measuring this return requires a more detailed examination of the funding process.

3.2.1 How Research is Funded

Private colleges and universities fund their operations primarily through tuition, federal grants, philanthropic donations, and auxiliary enterprises (like healthcare and athletics). For public universities, state appropriations also account for a significant share of incoming cash flow. Schools then use these funds mainly for student instruction, research, administration, and running the auxiliary programs. They budget operational expenses on an annual basis[7]

[6] Vergano, Dan. "Science Faces Sequestration Cuts." USAToday, February 25, 2013. http://www.usatoday.com/story/tech/sciencefair/2013/02/25/budget-nih-collins/1947277/ (accessed December 2, 2014).

[7] We use the word "operational" to separate these from capital expenses, like construction projects, which are likely to be budgeted long ahead of time.

and typically follow a June rather than December fiscal year end to synchronize with the course-year calendar.[8] The unused portion of funds are rarely allowed to carry over to the next year.[9]

The budgeting process is complicated by widespread earmarks. Strict guidelines on how funds can be spent are attached to a large portion of incoming cash flow, creating a distinction between "restricted" and "unrestricted funds."[10] Some earmarks are obvious: an NSF grant will go directly to the project for which it was awarded and state appropriations will directly subsidize instruction of in-state residents. Other earmarks are not so straightforward. A multi-million dollar donation by a wealthy single donor or a foundation could carry with it the requirement that it be used to extend hours at an art museum or gymnasium, increase a particular genre of books in the library, or expand the student center. For example, in 2010 Harvard University received a restricted gift of $50 million from the Tata family to fund two new buildings on the business school campus.[11] For both bookkeeping and flexibility reasons, these unrestricted funds are a precious commodity.

For research, unrestricted funds are often the "source of last resort." They are needed when costs run over, other sources fall short, or faculty are too new to have attracted sufficient grant money. That is, although federal and state funds still account for the majority of university-led R&D, they are frequently too slow or inflexible to handle the immediate and diverse needs of academic scholars. In the absence of unrestricted funds to close the gap, research is often put on hold. Murray [2013] identifies philanthropic donations as one possible channel for research institutions to fill funding gaps and provides a great example: in 2008, when the fiscal crisis forced the State of California to reduce funding to the UC Berkeley's Radio Astronomy Lab and federal government cut funding for Allen

[8] There are a few exceptions to the June fiscal year end but these too end in the summer months and are immaterial for our discussion.

[9] Carolyn Porter (Director of Development, McDonald Observatory, University of Texas at Austin), telephone conversation with authors, July 2014.

[10] We thank Kyle Welch for bringing this to our attention.

[11] Walsh, Coleen. "Business School Announces Tata Gift; Two Initiatives." Harvard Gazette, October 14, 2010. http://news.harvard.edu/gazette/story/2010/10/hbs_gift/ (accessed December 2, 2014).

Telescope Array, Microsoft's Paul Allen stepped in and donated funds to ensure continuous operation of the facility.[12] Combined with other, both large and small philanthropic gifts, unrestricted funds can also allow for scientific research to continue when federal financial support for science does not deliver. Other sources of unrestricted funds include auxiliary operations, like athletics and healthcare, housing, and tuition (primarily for out-of-state residents in the case of public schools). Since it enables us to identify and precisely estimate the elasticity of research output, football's contribution is covered in detail below.

How Football Contributes Financially

> "We took direct dollars from the athletic budget and put it into academic programs."
> E. Gordon Gee, 11th and 14th President, Ohio State University[13]

Football contributes to unrestricted university finances in two ways. The first channel is auxiliary revenues. Since the late 1980s, Division I NCAA football has generated over $10 billion in sales. For perspective, Table 3.1 provides the top 20 college football teams in terms of revenue. The sheer size of these programs is staggering, especially in relation to professional teams. For example, The University of Texas at Austin earns nearly $110 million in revenue. For comparison, this figure is 40% higher than the median professional hockey team and on par with the median professional basketball team. On a per game basis, it is 5 times larger than both of these and about 7 times larger than the median baseball team. Their size relative to total tuition is also quite large. More than half of the schools on the list have football programs that are more than 20% of the total tuition receipts. At Louisiana State University and Agricultural and Mechanical College (LSU), the University of

[12]Murray [2013] emphasizes three key points about science philanthropy: that it is mostly channeled into restricted funds, that it heavily favors translational science, and that it generally does not strive to fill funding gaps. However, it is important to note that her study focuses on large philanthropic gifts (>$1M) at top 50 research institutions and provides only one part of the funding equation. Some of these large philanthropic gifts happen to be unrestricted, and universities also collect many small philanthropic gifts which are usually unrestricted in nature. For example, the Harvard Alumni Association webpage provides opportunities for alumni to donate directly to the various university funds, most of which are unrestricted.

[13]"Dropping The Ball: The Shady Side Of Big-Time College Sports," The Bob Edwards Show (Washington D.C.: Public Radio International, January 4, 2015).

Nebraska-Lincoln, and the University of Oklahoma Norman Campus, this figure is nearly a third. Football also dwarfs other athletics in this sample. With only three exceptions, football contributes more to athletics revenue than all other sports combined. This is generally true outside of the current sample, too. Despite the popularity of college basketball, for example, its financial importance pales in comparison to football across virtually all US schools.

Table 3.1: *Football and university finances*

	Football			# Seasons	
		As a percent of all			
	Revenue	Athletics Revenue	Tuition Receipts	Ranked 1 or 2	Unranked
(NCAA Football: 12 game season)					
The Univ of Texas at Austin	$109,400,688	66%	23%	2	9
The Univ of Alabama	88,660,439	62%	25%	2	9
Univ of Michigan-Ann Arbor	81,475,191	66%	9%	1	5
Univ of Notre Dame	78,349,132	72%	29%	3	10
Univ of Georgia	77,594,300	79%	23%	1	9
Auburn Univ	75,092,576	73%	26%	2	8
Univ of Florida	74,820,287	58%	23%	4	2
Louisiana State Univ A&M College	74,275,838	63%	32%	2	10
Univ of Oklahoma Norman Campus	69,647,986	56%	31%	1	9
Univ of Arkansas	61,492,925	62%	8%	0	12
Ohio State Univ-Main Campus	61,131,726	49%	4%	4	4
Pennsylvania State Univ-Main Campus	58,722,182	56%	9%	1	8
Univ of Washington-Seattle Campus	56,379,534	66%	32%	1	13
Univ of Nebraska-Lincoln	55,866,615	64%	16%	3	5
Univ of Iowa	55,648,679	52%	20%	0	12
The Univ of Tennessee	55,359,423	50%	17%	1	8
Univ of Oregon	53,982,076	66%	13%	1	12
Texas A & M Univ-College Station	53,800,924	69%	27%	0	10
Univ of Wisconsin-Madison	50,641,993	35%	8%	0	12
Michigan State Univ	47,869,615	60%	5%	0	16
(For comparison)					
Median Pro Football Team (16 game season)	$269,000,000				
Median Pro Baseball Team (162 game season)	214,000,000				
Median Pro Basketball Team (82 game season)	139,000,000				
Median Pro Hockey Team (82 game season)	80,500,000				

Source: NCAA.org (college athletic revenue), US Dept of Education National Center for Education Statistics (tuition), Associated Press (team rankings), and Forbes.com (professional sports revenue).

A share of these revenues are returned to the general university fund and ultimately support academic endeavors. For example, in 2012, the Louisiana State University team pledged over $36 million over 5 years to support the school's academic mission. In 2005, the

Notre Dame football used $14.5 million of its post-season bowl winnings to fund academic priorities. From 2011 to 2012, the University of Florida team gave $6 million to cover shortfalls in university funding [Dosh, 2013]. From 2012 to 2013, the University of Texas - Austin gave $9.2 million of its $18.9 million back to the university fund while the University of Nebraska - Lincoln did the same with $2.7 million of its $5.2 million surplus [Lavigne, 2014].

The second channel is alumni contributions. Football success is a major catlyst for philanthropic fundraising shocks [Meer and Rosen, 2009, Anderson, 2012]. For example, Texas A&M University raised more money the night after its freshman quarterback, Johnny Manziel, won the Heisman Trophy than it typically raises in a full month. That year, the school announced it received a record-setting $740 million in donations[14]. The university chancellor John Sharp highlighted the significant role college football played in their fund-raising efforts, stating, "Football is one heck of a megaphone for us to tell our story".[15] Schools also can directly tie athletic privileges to academic donations. Stinson and Howard [2010, 2014] document how one large Midwestern school makes donors of academic gifts over $3,000 eligible to buy season tickets.

Football success, and most likely its financial contribution, are quite volatile. This is shown in the rightmost two columns of Table I. Sixteen of the twenty schools have competed for the national championship over the panel 1987 to 2012. On the other hand, every team was unranked at least twice over the panel, and many were unranked more than ten times. These reversals of fortune are important because variation in teams' rank provides the underlying variation for our identification. For example, a surprising 11-0 record of Boise State University football team in 2004-2005 resulted in an marked increase in university donations, a 66% increase in sales of university merchandise at the bookstore, and a 60%

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[14] Marty Holmes (Vice President, The Association of Former Students, Texas A&M University), telephone conversation with authors, July 2014.

[15] Troop, Don. "Texas A&M Pulls in $740-Million for Academics and Football." The Chronicle of Higher Education, September 16, 2013. http://chronicle.com/blogs/bottomline/texas-am-pulls-in-740-million-for-academics-and-football/ (accessed December 2, 2014).

increase in sales of the subsequent year's seasons tickets [Grant et al., 2008].

3.3 Data

3.3.1 Sources

We draw data from four sources. The first is vote data from the Associated Press (AP) Top 25 Poll, which we use to construct our instrumental variable. The poll surveys sixty-five sportswriters and sports broadcasters. Each provides a ranking for the top twenty-five teams from NCAA Division I. Each team receives 25 points for each 1st place vote, 24 points for each 2nd place vote, and so forth, and the votes are aggregated over survey responses.[16] The AP publishes the vote totals of all teams. Ballots are collected weekly through the season, with results made public and published at the end of the week. We measure the within-season change in team quality by subtracting pre-season votes from end-of-season votes. Polls varied slightly in the number of voters and, in 1987 and 1988, the number of points allocated, so we normalize the measure by standard deviation. This data is widely disseminated each week of the season and has a special place in college football; unlike professional sports or other college athletics, which rely on playoffs and divisional rank and record, polls were the sole source of determining an NCAA football champion until 2013.[17] At least three other polls are widely published, although the AP Poll is the best known. Moreover, although they are closely correlated, the other major polls had obvious limitations for our setting.[18] The relevant time variable for this data is the fiscal year in which a season is wholly contained. Fiscal years coincide with the academic calendar for schools in our data.

The second component is academic publishing data. Thomson Reuters Web of Science

[16]The exception is for 1987 and 1988, where voters ranked only the top 20 teams. For these polls, teams received 20 points for each 1st place vote, 19 points for each 2nd place vote, and so forth.

[17]In 2014, a playoff system was instituted.

[18]The BCS Poll, for example, did not cover our full sample. The Coaches Poll could, hypothetically, be contaminated by strategic voting. Other polls were much less widely known and relied upon.

collects this for their Incites database product. We extract a count of the scholarly articles published and a count of the citations that accrue to those articles (up to the date of data retrieval). Observations are specific to a calendar year, institution, and academic discipline. Since the instrument only has variation at the institution-year level, we aggregate up to this level by taking a sum over all science disciplines, excluding social sciences and medicine.[19] Although including the latter two categories improves power in our first stage, it can bias our estimates away from the elasticities of interest.[20]

The third component is US patent application data. Thomson Reuters collects this for their Thomson Innovation database. It allows us to identify university patentees better than the raw USPTO patent records. We use the browse feature in Thomson Innovation Assignee/Applicant search field to identify all possible university name variations together with unique 4-letter Assignee Codes identifying one of approximately 22,300 patenting organizations worldwide. This enables us to count and aggregate patent applications wherever a college or university appears as an assignee or applicant on the patent record. Again, we extract a count of new patent applications filed and a count of the citations that accrue to those patents (up to the date of data retrieval). Although patents are assigned into technological classes, there is no clear map to academic disciplines. Thus, we aggregate up to the institution-year level by taking a sum over all classes. We assemble this data on a fiscal year basis. More details on patent dataset construction are provided in the Appendix.

The final component is university research expenditure data. The National Science Foundation (NSF) collects this data annually in their Higher Education Research and Development Survey (prior to 2010, called the Survey of R&D Expenditures at Universities

[19] For the Incites database, this includes physics, chemistry, mathematics, computer science, biology and biochemistry, microbiology, plant and animal science, agricultural science, geoscience, environmental science, and ecology.

[20] Social sciences are not central to the current policy debate. They also tend to have longer and more dispersed publication lags relative to non-social sciences, which will bias our coefficient estimates downward (unless we take a much stronger stand on the timing). In the same vein, medical research will include a large number of development applications relative to the other natural sciences. Unrelated to these, we are also forced to exclude space science, which includes astronomy but is dominated by aerospace and aeronautical engineering.

and Colleges). Responses are carefully reviewed and verified as needed.[21] The survey is an annual census of all institutions spending at least $150,000 in separately budgeted R&D. The data is broken down by federal and non-federal sources as well as by disciplines. Our first expenditure measure is tied to scholarly articles, so as with the Thomson Incites data, we take a sum over all science disciplines, excluding social sciences and medicine.[22] Our second expenditure measure is tied to new patent application filings, which are not discipline specific, so we take a sum over all non-social science, engineering, and medical disciplines. This data is on a fiscal year basis.[23]

Panel Length and Scope

The instrument is based on the difference between post-season and pre-season votes. Since the median NCAA team receives zero votes, using the universe of teams would result in a very large number of zero values. So that the schools are selected agnostically and the instrument has power, we simply order the teams by the sum of the absolute value of their vote changes and select the top forty schools for our panel. This is exactly $\frac{1}{3}$ of the 120 Division I teams. The only caveat is that if there are heterogeneous treatment effects, our estimates pertain only to schools with large football programs. The resulting list is very diverse. It includes private (e.g. Stanford, Notre Dame) and public (e.g. Alabama, Nebraska) institutions as well as relatively small (e.g. Boise State) and large (e.g. Texas) ones. Figure

[21] In two cases where we needed clarification, the NSF had also asked for them. This gave us confidence that the data was thoroughly reviewed and validated by the NSF. Ronda Britt at the National Center for Science and Engineering Statistics was particularly helpful. Our main issue was missing values for Boise State University prior to 1992 and in 2005 and 2006. In the earlier years, the institution was below the survey threshold. For the later two years, the NSF followed up with the school and confirmed it made an error in reporting due to a personnel change. We omit these years from our analysis, although the results are robust to dropping this institution entirely.

[22] For the NSF data, this includes physics, chemistry, and mathematics and statistics, computer science, biological sciences, and other life sciences, agricultural sciences, geosciences, oceanography, atmospheric sciences, and earth sciences.

[23] This includes all departments from the first measure, as well as medical sciences (including clinical medicine, immunology, pharmacology and toxicology, and molecular biology), engineering (including aerospace, chemical, civil, electrical, materials, mechanical, and other), interdisciplinary and other sciences, and astronomy (which, along with aerospace engineering, would be classified as "space science" in the Incites database).

3.5 shows geographic distribution of schools by type. The magnitudes of our estimates are not very sensitive to the size of the panel.[24]

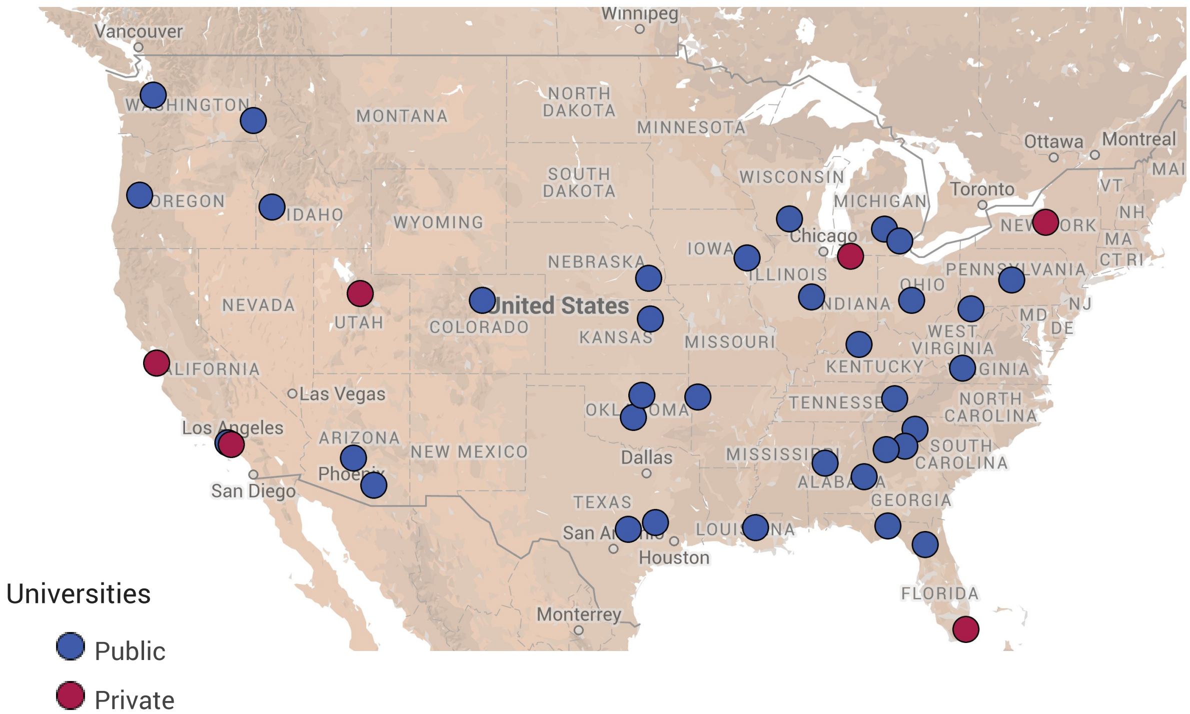

Figure 3.5: *Geographic distribution of schools by type*

The beginning of the panel coincides with the start of the "modern era" of college football, which traces back to the 1984 Supreme Court ruling on *NCAA v. Board of Regents of the University of Oklahoma*.[25] Prior to the ruling, the NCAA restricted the number of games that could be broadcast, threatening non-complying schools with an association-wide boycott. In 1981, two schools challenged the NCAA's authority and in 1984, the Burger court ruled that the NCAA violated antitrust laws by controlling television broadcasting rights. Effectively, schools and their conferences were now free to negotiate directly with broadcasters. Broadcast networks treated the first year or two as a trial for the new

[24]Clearly, shrinking the list of schools far below forty simply limits statistical power across all specifications, while expanding the list far beyond forty introduces many zeros to the instrument thus weakening it substantially.

[25]See *NCAA v. Board of Regents of the University of Oklahoma*, 468 US 85 (1984).

arrangement, but by 1987 the number of televised games and the exposure of the league surged, leading to an unprecedented financial gain. That year featured the highly contentious Fiesta Bowl, which became one of the most watched college games in history, and marks the start of our panel of football outcomes.[26] Data on scholarly articles begin on the same date, while the patent data begin in 1996. Although we observe data for earlier periods, the international harmonization of the Unites States patent system in the early 1990's created a large spike in the number of filings and seemingly increased the overall level of patenting. If the response of patenting behavior to research funding was different prior to 1996, and the goal is to recover parameter estimates that are informative for current policymaking, then including data on filings prior to 1996 will lead to the wrong parameter estimates. The dataset ends in 2011. While 2012 data was available for our outcome measures, scholarly articles and patents have had so little time to attract citations and the resulting drop off is so steep that these additional points create essentially only noise. Moreover, there is a chance that patent applications filed in 2012 have not yet been recorded as of the writing of this paper. This leaves 23 and 16 years of observations for scholarly articles and patents, respectively.

3.3.2 Summary Statistics

First, we summarize the data by institution. There are forty in total. Texas A&M - Main Campus spends the highest amount on non-social non-medical science research, at $132 million, followed by the University of Georgia. The mean level is $49 million. Texas A&M - Main Campus also spends the most in total non-social science and engineering, at $259 million, followed closely by the University of Wisconsin - Madison. The mean level is $98 million.

[26]The game pitted Penn State against a heavily-favored University of Miami. The pre-game antics of Miami, including dressing in military fatigues for the flight to the game, and controversial remarks by both sides at a joint team dinner the night before the game contributed to wide-spread media attention. For the first time in history, a sitting US President (Ronald Reagan) was interviewed at the halftime show. Penn State won 14-10. The national press coverage of the players, coaches, their backgrounds, and the developments leading up the game are all common in the "modern era" but were unheard of prior to 1987.

The University of Wisconsin-Madison publishes the highest number of scholarly articles, at an average of over 1,800, followed by the Stanford University and the University of Michigan, Ann Arbor. The average number is 820. Stanford University also has the highest average number of related citations, at an average of over 61,000, followed by the University of Wisconsin-Madison and the University of Washington (main campus). The average number is 22,336. Stanford University tops the list of new patent application filings and the citations that accrue to them, at 156 and 3,429, respectively. The University of Texas at Austin is second, with 117 and 2,205, respectively. The mean levels are 34 and 570, respectively.

Next, we summarize the data by year. The average level of non-social non-medical science expenditures grows from $24 to $75 million from 1987 to 2011, while the average level of total non-social science and engineering expenditures grows from $41 to $165 million over the same period. This is an average compound growth rate of 5% for the former funding measure and 6% for the latter. The funding measures are monotone increasing over the panel, with a few exceptions. In 1994, 2004, and 2010, both funding measures drop relative to the year before (in nominal terms). These years directly follow the peak unemployment periods of the last three US recessions.[27] Over the same period, scholarly articles grow at 3.2% while patent applications grow more than twice as fast, at 7.2%. There is considerable variation across schools within each year, but both variables tend to increase monotonically over the panel. The time series of citations is more complicated, since the amount of time other work has to cite these articles and applications is falling over the panel. Both citations are monotonically increasing up to and including 1998 and then monotonically decreasing after and including 2005. In any case, all main empirical specifications below include year fixed effects, so these issues should not present a problem.

[27]Peak unemployment hit 7.8% in 1992, 6.3% in 2003, and 10.0% in 2009 for the 1990s recession, 2000s recession, and "Great Recession," respectively. Source: "Business Cycle Expansions and Contractions." NBER Website. March 5, 2015.

3.4 Empirical Model

3.4.1 Overview

We aim to better inform policymakers and administrators about the impact to scientific output from an additional dollar of investment in university research. Estimating this requires addressing two empirical issues. The first comes from the fact that high quality institutions attract big grants as well as big ideas. This causes parameter estimates to be upward biased and suggests that, at a minimum, removing the institution-specific means and time trends from the data is required. However, this still leaves open the question of endogeneity and, as Adams and Griliches [1998] note, probably exacerbates the second issue, an errors-in-variables problem. When the data include long-term projects with multi-year payoffs, tying research outcomes to the expenditures that generated them becomes difficult. Even if a tight causal relationship exists, estimating it can be impossible without information that the econometrician rarely has access to. In the case of the multi-billion dollar Large Hadron Collider at CERN, construction began ten years prior to the first experiments. In the case of the Stanford Linear Accelerator Center, researchers still benefit from portions of the initial $114 million investment in 1961.

The solution is to find a quantity in the data generating process that shifts only marginal research funds and yet is not correlated with the time-varying quality of the institution. To achieve this, we use unexpected NCAA football outcomes. Unexpected wins, for example, shift out research funds and, in turn, drive scientific discovery. Football presumably has a negligible effect on the ability of a school to conduct cutting edge research, and so is excluded from the outcome variables except through funding—especially one or two years into the future.

Timing

Our assumptions regarding the temporal relationship between the variables are as follows: football outcomes impact the level of research in the subsequent period and scholarly articles in the period subsequent to that. Since patent applications usually need to be filed with the USPTO prior to discussing findings in a public forum, i.e. seminar or conference, the patent filings are typically concurrent with the research. Figure 3.6 illustrates these relationships using our first year of data.

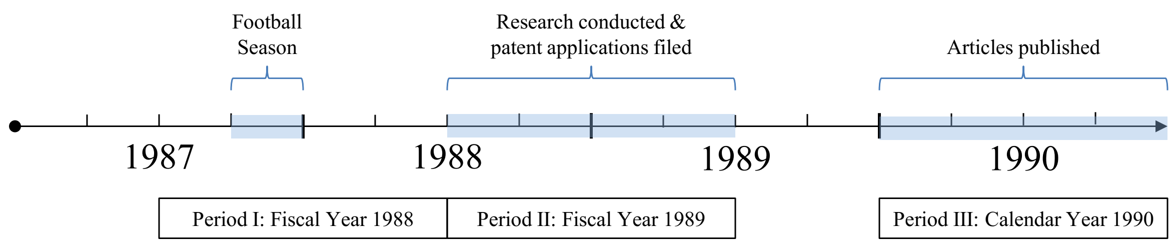

Figure 3.6: *Timing of football, research, and publishing*

The first period is fiscal year 1988. This period covers regular season football, which is played in the fall of 1987, as well as post-season football, which is played in January of 1988. Football outcomes impact incoming unrestricted funds during this period, including playoff "bowl" proceeds, alumni donations, and the pre-sale of the next season's seats and broadcasting rights. Changes in these incoming funds are budgeted out and spent in the following period, fiscal year 1989. Research is conducted. Alongside or immediately following the research, scientists file patent applications, which must legally precede any dissemination of the findings. The final period is calendar year 1990. Successful research carried out in the second period will be published in journals during this period. The temporal relationship between football, expenditures, and publishing is an assumption we discuss in detail in a later section.

3.4.2 Specification

The first stage assesses the relationship between the instrument and the endogenous regressor. Specifically, we estimate the following:

$$LogNonFedExpenditures_{i,t} = \alpha_0 + \alpha_1 Football_{i,t-1} + \mu_i + \delta_t + \gamma_i t + \nu_{i,t} \tag{3.1}$$

where i denotes institution, t denotes the fiscal year, $LogNonFedExpenditures$ denotes the log of non-federal research expenditures, $Football$ denotes the difference between postseason and preseason Associated Press votes (standardized across polls), μ and δ denote school and time dummies, and γ captures the school-specific time trend (omitting the superscripts). We use first stage estimates, $(\hat{\alpha}_0, \hat{\alpha}_1, \hat{\mu}_i, \hat{\delta}_t, \hat{\gamma}_i)$, to generate predicted values for $LogNonFedExpenditures_{i,t}$, denoted $Log\widehat{NonFedExpenditures}_{i,t}$.

To estimate the dollar elasticity of scientific output, we regress the log of each of our four output measures on the predicted values from the first stage. The four estimating equations are given by the following:

$$LogArticles_{i,t} = \beta_0^1 + \beta_1^1 LogNon\widehat{FedExp}enditures_{i,t-1} + \kappa_i^1 + \phi_t^1 + \lambda_i^1 t + \epsilon_{i,t}^1 \tag{3.2}$$

$$LogArticleCites_{i,t} = \beta_0^2 + \beta_1^2 LogNon\widehat{FedExp}enditures_{i,t-1} + \kappa_i^2 + \phi_t^2 + \lambda_i^2 t + \epsilon_{i,t}^2 \tag{3.3}$$

$$LogPatents_{i,t} = \beta_0^3 + \beta_1^3 LogNon\widehat{FedExp}enditures_{i,t} + \kappa_i^3 + \phi_t^3 + \lambda_i^3 t + \epsilon_{i,t}^3 \tag{3.4}$$

$$LogPatentCites_{i,t} = \beta_0^4 + \beta_1^4 LogNon\widehat{FedExp}enditures_{i,t} + \kappa_i^4 + \phi_t^4 + \lambda_i^4 t + \epsilon_{i,t}^4 \tag{3.5}$$

where κ and ϕ denote school and time controls and λ captures the school-specific time trend (again, omitting superscripts). (2) and (3) use lagged expenditures while (4) and (5) use contemporaneous expenditures. For identification, we require that $Football_{i,t-1}$ is uncorrelated with $\epsilon_{i,t+1}^1$, $\epsilon_{i,t+1}^2$, $\epsilon_{i,t}^3$, and $\epsilon_{i,t}^4$, and that $Football_{i,t-1}$ is a sufficiently strong predictor of $LogNonFedExpenditures_{i,t}$. We cluster our standard errors at the university level, which allows for arbitrary correlation of the unobservables within a university over time, i.e. the squared sum of regressor and error are required to have the same distribution across clusters. In theory, we could also allow for arbitrary correlation of the unobservables within-year in the same specification, as utilized in Petersen [2009], but this is too steep a requirement of the data. As one of our robustness checks, we tested an alternative specification that clustered at the year level and resulted in smaller standard errors, so we did not include these results (although they are available on request). β_1 is the parameter of interest.

We also estimate the dollar cost of a patentable idea (or, to be precise, an idea that the researcher and institution deem worthy of a patent application). To translate the elasticity estimate into level changes, we multiply the reciprocal of this elasticity—roughly the percent change in research expenditures required per one percent change in patent applications—by the average ratio of expenditures to applications. Thus, the cost estimate equals

$$\frac{1}{N}\frac{1}{T}\sum_i\sum_t \hat{\beta}_1^3 \frac{NonFedExpenditures_{i,t}}{Patents_{i,t}}$$

where N is the number of schools.

There are two potential concerns about the exclusion restriction. Both seem small. One occurs if unexpected college football outcomes drive research outcomes, whether in the laboratory or publication process. This includes the case where, for example, football success may attract researchers that are inherently more productive on average. Previous work like Anderson [2012] has shown that the undergraduate student body does improve after teams win. This same argument is unlikely to hold for graduate students and faculty. Another occurs if a third factor simulatenously improves both football and research outcomes, but goes unnoticed by the Associated Press voters. Since the reputation and career prospects of these sports writers and broadcasters depend on the accuracy of their predictions and their perceived access to information, this also seems unimportant. Nonetheless, evidence in the "Exogeneity Check" section provides further support for the instrument.

3.5 Results

3.5.1 From Football to Money

Our first stage results assess the relationship between unexpected football outcomes and research expenditures. Table 3.2 reports these results. Each specification includes university and time fixed effects as well as university-specific time trends. Columns 1-2 show that a one thousand unit change in the vote difference would increase non-medical non-social science expenditures by 3.3% and total non-social science and engineering expenditures by 2.6%. These estimates are significant at 99.6% and 97.5% levels, respectively. Columns 3-4 show that this same change would increase non-medical non-social science expenditures by $1.775 million and total non-social science and engineering research expenditures by $1.966 million. The first of these estimates is significant at the 99.3% level, but the second is not precisely estimated. The fit of these specifications range between 95% and 98%, which is not surprising given the large number controls.[28]

Table 3.2: *The impact of football on non-federal research expenditures*

	Non-medical Non-social Science		Non-social Science and Engineering	
Dep. Var.:	Log of Expend.	Level of Expend.	Log of Expend.	Level of Expend.
	(1)	(2)	(3)	(4)
1000 Vote Change	0.0327***	1,775***	0.0256**	1,966
	(0.0108)	(618.3)	(0.0110)	(1,226)
Constant	115.9***	1.053e+07***	124.2***	2.983e+07***
	(0.185)	(10,376)	(0.190)	(19,981)
School FE	x	x	x	x
Year FE	x	x	x	x
School Time Trend	x	x	x	x
R-squared	0.965	0.956	0.976	0.963
Observations	949	949	949	949
Number of Clusters	40	40	40	40

*Note: Standard errors, clustered at university level, in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.*

These estimates square with stylized facts about college football and finances. A one thousand vote change is approximately equal to, for example, a move from 17th place to 1st place or from an unranked position to 10th place. The comparison is imperfect, but this translates to a $60 million revenue change in Table 3.1. Our discussions with

[28] Raw vote differences are used here so the coefficients can be easily interpreted. In the 2SLS results below, vote differences are normalized across years to improve comparability and improve power.

administrators suggest that roughly five to ten percent of cash flow changes find their way back to university research, and translate into somewhere between \$3 million and \$6 million of additional funding. Since funds are shared between social and non-science departments, and since higher revenues translate to higher costs—for example, hiring more security guards at games to monitor larger crowds at games—then our estimates are in line with what one would expect.

3.5.2 From Money to Scholarly Articles

To assess the impact of money on science, we begin with the relationship between research expenditures and academic publishing behavior. Table 3.3 reports these results. This table, as well as the three that follow, present the OLS estimates in the first five columns and the 2SLS estimates in the latter five. Our main findings are in the final column. We find that the dollar elasticity of scholarly articles is 0.310, after controlling for school and time fixed effects as well as school-specific time trends. The instrument, lagged unexpected college football success, provides exogenous variation to science and engineering research expenditures sourced from the university. The estimate is significant at 99.2%. The F-statistic of the accompanying first stage is 10.98.

The sharp contrast with the OLS results is striking. Our main elasticity estimate is nearly ten times what results from an OLS specification with the same level of controls, which would lead policymakers to underestimate the returns to funding scientific research and presumably under-invest in it. One potential issue is that the instrument is identifying a local average treatment affect that is substantially higher than the average elasticity of the sample schools (or sample school-years). This would happen if the sensitivity of the schools' budgets to football outcomes are correlated with the schools' elasticity. If anything, we would expect this to go in the opposite direction—with schools transforming dollars to discoveries at the highest rates also being the schools whose budgets are least affected by football.

More likely the issue is a rather serious errors-in-variables problem for the OLS. The

Table 3.3: *The impact of money on scholarly articles*

	OLS Specifications					IV Specifications				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Lagged Log Expenditures	0.456***	0.438***	0.438***	0.0658**	0.0349**	0.596	0.603	0.442	0.471	0.310***
	(0.0962)	(0.105)	(0.0419)	(0.0280)	(0.0171)	(0.486)	(0.502)	(0.481)	(0.326)	(0.117)
Constant	1.930*	2.220*	0.719**	3.559***	1.313***	0.485	0.449	1.158	0.981	1.233
	(1.038)	(1.168)	(0.289)	(0.208)	(0.189)	(5.046)	(5.437)	(4.690)	(3.326)	(1.210)
School FE			x	x	x			x	x	x
Year FE		x		x	x		x		x	x
School Time Trend					x					x
Observations	869	869	869	869	869	869	869	869	869	869
R-squared	0.422	0.433	0.956	0.983	0.994	0.382	0.382	0.956	0.966	0.989
Number of Clusters	40	40	40	40	40	40	40	40	40	40
F-Stat: 1st Stage						2.73	2.45	1.54	5.36	11.11

*Note: Standard errors, clustered at university level, in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.*

difficulty in temporally tying budgets to discoveries is at the heart of the problem. For example, portions of the $114 million investment in the Stanford Linear Accelerator, built in 1961, generated research for years afterwards. In projects like this, operating expenses may precede experiments for many years, weakening the link between research budgets and articles in the subsequent year and attenuating the elasticity estimates.

To explore this point further, we remove institution specific controls. In fact, removing the institution-specific time trend alone results in a nearly tenfold increase in the estimated elasticity (without much relative change in precision). It is, unfortunately, impossible to say whether the sharp rise is attributable to the mitigation of the errors-in-variables problem or to the re-introduction of institution specific unobservables that drive both expenditures and scientific output. Removing the institution or year fixed effects does not further change the estimates much. It seems that whatever the relative contribution of the errors-in-variables problem or the omitted variable bias may be, their combined effect varies in a complicated way—over time and within the institution.

Our pooled OLS estimates are at the bottom end of those found by Adams and Griliches [1998]. In the presence of only time fixed effects and three high-level institutional controls (for top ten public university, top ten private university, and other private university), they find a dollar elasticity of scholarly articles of between 0.4 and 0.7. The school fixed effects also have the same impact on their OLS results that they have on ours: they find an elasticity of roughly zero.

There is one important caveat for policymakers who wish to use these numbers to predict returns to an aggregate national increase in research funding. Since the predicted variation in expenditures is linear in the instrument, unexpected losses hurt research budgets as much as unexpected wins help them. Thus, our instrument transfers money between schools without shifting aggregate annual spending on a national level up or down. If these money transfers are merely moving scarce assets between institutions, and if these scarce assets—like highly productive scientists—are inelastically supplied in the short-run, then our estimates would not be very informative about how scientific output responds to aggregate funding increases.[29] However, this is unlikely. Small and temporary shifts in funding do not drive expensive, long-term commitments like faculty hiring. Faculty also, by casual observations, are not perfectly mobile. Finally, since successful scientists tend to attract federal grants, their movement from one institution to another would also shift federal research spending. However, our exogeneity check below reveals this is not the case. Instead, our conversations with administrators and reseachers suggested an increase in purchases of materials and technical staff hires as the most likely outcome. They also suggested the technical staff hires not to have, or be in a pursuit of an advanced degree, since new doctoral students and post-doctoral fellows are similar to new faculty hires and represent long-term and costly commitments. While important, the investigation of detailed institutional fund allocation mechanisms is beyond the scope of this paper and we leave it for future research.

3.5.3 From Money to Scholarly Article Citations

Next, we consider the citations that accrue to the aforementioned articles. Table 3.4 reports these results. We find that the dollar elasticity of article citations is 0.590. The result is significant at 97.2%.

The larger coefficient on citation-weighted articles squares with intuition. Scholars make extensive-margin decisions about whether to take on more projects. They also make intensive-margin decisions about how much to invest in those they already plan to take on. The article count can be thought of as this extensive margin while the citation-weighted count captures both. To see this, considering the limiting case where researchers facing windfall funding invest only in improving projects they already plan to take on: the number of articles would show no change while the citation-weighted count would fully-reflect the investment. The fact that the citation weighted estimate is close to twice the no-weight estimate suggests scholars are splitting the investment across these margins.

[29] A large, aggregate funding increase aimed towards academic institutions could attract scientists away from the private sector or from abroad. However, neither one of these outcomes seems like a first-order policy goal.

Table 3.4: *The impact of money on scholarly articles' citations*

	OLS Specifications					IV Specifications				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Lagged Log Expenditures	0.374***	0.435***	-0.243***	0.0743	0.0574	0.651	0.798	1.059	0.426	0.590**
	(0.135)	(0.137)	(0.0697)	(0.0535)	(0.0370)	(0.659)	(0.716)	(1.331)	(0.502)	(0.268)
Constant	5.897***	4.080**	7.900***	4.700***	18.05***	3.037	0.166	-2.084	2.914	16.07***
	(1.450)	(1.518)	(0.480)	(0.395)	(0.654)	(6.813)	(7.739)	(12.97)	(5.120)	(2.736)
School FE			x	x	x			x	x	x
Year FE		x		x	x		x		x	x
School Time Trend					x					x
Observations	869	869	869	869	869	869	869	869	869	869
R-squared	0.179	0.349	0.850	0.962	0.985	0.081	0.191	0.594	0.954	0.974
Number of Clusters	40	40	40	40	40	40	40	40	40	40
F-Stat: 1st Stage						2.73	2.45	1.54	5.36	11.11

*Note: Standard errors, clustered at university level, in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.*

This is, of course, only one possible interpretation, and Adams and Griliches [1998] propose two interesting alternative views. The first is that as Ph.D. students become junior faculty at smaller schools, papers derived from their doctoral work will be incorrectly attributed to the school that hired them. However, this problem will be partially corrected if these papers happen to cite scholars at their degree-granting institution. The second is that larger programs tend towards basic research, which is more likely to have "hit" papers. We prefer our interpretation of the relative magnitudes since the ratio of articles to citations is robust to the inclusion of institution fixed effects and institution-specific time trends.

The errors-in-variables problem discussed in the preceding section again seems an issue for OLS specifications. Although the pooled OLS specification yields a relatively precise estimate of 0.374, the addition of the full set of controls yields an imprecise estimate of 0.057. These results are, again, near the bottom end of the Adams and Griliches [1998] range. They find a dollar elasticity of article citations of between 0.6 and 0.9 without school fixed effects but close to zero effect with school fixed effects.

3.5.4 From Money to Patents

To assess the impact of money on translational and applied science output, we assess the relationship between research expenditures and patenting behavior. Table 3.5 reports these results. We expand our funding data to encompass total non-social science and engineering disciplines, rather than non-medical non-social science only.[30] We find that the dollar elasticity of patent applications is 1.91. This result is significant at 96.2% and the corresponding first stage F-statistic is 11.18. This elasticity is surprisingly high and implies increasing returns to research spending, i.e. for each proportional increase in research expenditures, new patent applications will rise by more than 1%. The contrast with the OLS coefficients are even more striking than in the case of scholarly publications. Here, the elasticity from the main specification is between two and three times the precisely-estimated

[30]The University of Oregon was the only school in our sample without an identifiable Assignee/Applicant name or DWPI Assignee code in Thomson Innovation. Since the University of Oregon is also the only school in our sample without the School of Engineering, we drop it from the patent analysis portion of the paper.

OLS coefficient. Moreover, it is nearly one hundred times the imprecisely estimated OLS estimate with a full set of controls and more than twice the upper bound of the 95% percent confidence interval around that estimate.

We also estimate the dollar cost of generating a patentable idea. This entails dividing the ratio of non-federal research spending to patents by the elasticity estimated above, and averaging across schools and, where applicable, time. Using only the most recent years' spending-to-patent ratios yields a cost of $2.612 million. Using all years' ratios yields a cost of $2.975 million. University patenting has increased steadily since the Bayh-Dole Act of 1980, which allowed universities to retain ownership over their publically-funded intellectual property. Thus, the first figure should better predict the response to a current policy change. Despite broader coverage in terms of disciplines and a longer panel, these figures are quite close to—although slightly lower than—the roughly $3.3 million cost estimated in Azoulay et al. [2014].

3.5.5 From Money to Patent Citations

Finally, we assess the relationship between research expenditures and patent citations. Table 3.6 reports these results. Our main specification yields an elasticity of 3.30, and this result is significant at 98.8%. This estimate is nearly twice the elasticity on the count of patent applications, again suggesting researchers are roughly splitting their time between launching new projects and improving the quality of existing projects. Although the outcome data comes from an entirely separate source than the scholarly article data, it is reassuring to see the ratio of documents to their accrued citations be the same for both scholarly articles and patent applications.

Nonetheless, this suggests strongly increasing returns to research investment at the margin and may be surprising. However, when one considers the large amount of fixed investment, both in terms of faculty and facilities, then if the bottleneck for research—as recent press has indicated—is at the funding level, these elasticities both seem reasonable. Of course, while one would need to estimate the real returns from academic patents to

Table 3.5: *The impact of money on patent applications*

	OLS Specifications					IV Specifications				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Lagged Log Expenditures	0.690***	0.657***	1.017***	0.536***	0.0207	-0.0790	0.0460	2.014**	1.916**	1.914**
	(0.114)	(0.112)	(0.103)	(0.193)	(0.313)	(0.960)	(0.762)	(0.901)	(0.791)	(0.922)
Constant	-4.713***	-4.780***	-6.886***	-3.759**	-2.775	4.037	3.003	-20.08**	-19.29**	-19.23*
	(1.321)	(1.266)	(0.791)	(1.396)	(1.920)	(10.89)	(8.900)	(9.757)	(8.839)	(10.36)
School FE			x	x	x			x	x	x
Year FE		x		x	x		x		x	x
School Time Trend					x					x
Observations	607	607	607	607	607	607	607	607	607	607
R-squared	0.401	0.425	0.836	0.850	0.909		0.125	0.752	0.798	0.851
Number of Clusters	39	39	39	39	39	39	39	39	39	39
F-Stat: 1st Stage						5.58	4.81	2.90	6.17	11.10

*Note: Standard errors, clustered at university level, in parenthesis. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.*

Table 3.6: *The impact of money on patents' citations*

	OLS Specifications					IV Specifications				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Lagged Log Expenditures	0.609***	0.746***	-0.872***	0.816***	0.129	-0.0488	-0.110	2.251	2.539**	3.302**
	(0.0977)	(0.128)	(0.258)	(0.288)	(0.229)	(1.374)	(1.209)	(1.954)	(1.120)	(1.314)
Constant	-1.527	-2.077	9.529***	-2.006	1.322	5.954	5.366	-20.71	-25.97**	-35.06**
	(1.112)	(1.410)	(1.982)	(1.984)	(1.460)	(15.60)	(14.20)	(21.15)	(12.50)	(14.72)
School FE			x	x	x			x	x	x
Year FE		x		x	x		x		x	x
School Time Trend					x					x
Observations	604	604	604	604	604	604	604	604	604	604
R-squared	0.174	0.395	0.695	0.805	0.857		0.067	0.235	0.760	0.770
Number of Clusters	39	39	39	39	39	39	39	39	39	39
F-Stat: 1st Stage						5.58	4.81	2.90	6.17	11.10

*Note: Standard errors, clustered at university level, in parenthesis. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.*

figure out whether the government and universities are funding the right level of research, our results appear to support arguments for an increase in research spending.

3.5.6 Exogeneity Check

College football should impact only research funds provided by non-federal sources and have no effect on funds provided by the federal government. We observe the dollars contributed from these sources independently in the data and use this to strengthen the exogeneity argument for our instrument. That is, if some unobservable factor that varied by institution and time was driving unexpected football success, scientific discovery, and non-federal research funding, then it is likely to show up in federal research funding as well. Figure 3.7 addresses this potential confound. The y-axis shows research expenditures, by source, while the x-axis shows the instrument. School and year effects, as well as a schools-specific time trend, have been removed from both.

The left panel reports the strong, positive relationship between the instrument and research expenditures sourced from non-federal entities. This is merely the graphical representation of the first-stage results. The right panel, in contrast, reports the lack of any relationship between the instrument and federally-sourced research expenditures.

In fact, we can statistically separate the effect on these two sources. To do so, we pool together federal and non-federal data, so that an observation is university-year-source specific. We interact the full set of controls with a dummy variable for non-federal expenditures so that our university and year fixed effects as well as our university-specific time trends are source specific. The standard errors are clustered at the university-source level. Table 3.7 reports the results of this exercise. In the first column, the left-hand side variable is the log of non-medical non-social science expenditures. The instrument has a precisely estimated zero effect on the federally-sourced portion of expenditures. That is, the coefficient is not significant and the 95% confidence interval spans a relatively narrow range of -0.75% to 0.78%. In contrast, the coefficient on the interaction term—representing the impact of the instrument on the non-federally-sourced portion of expenditures—is positive and significant

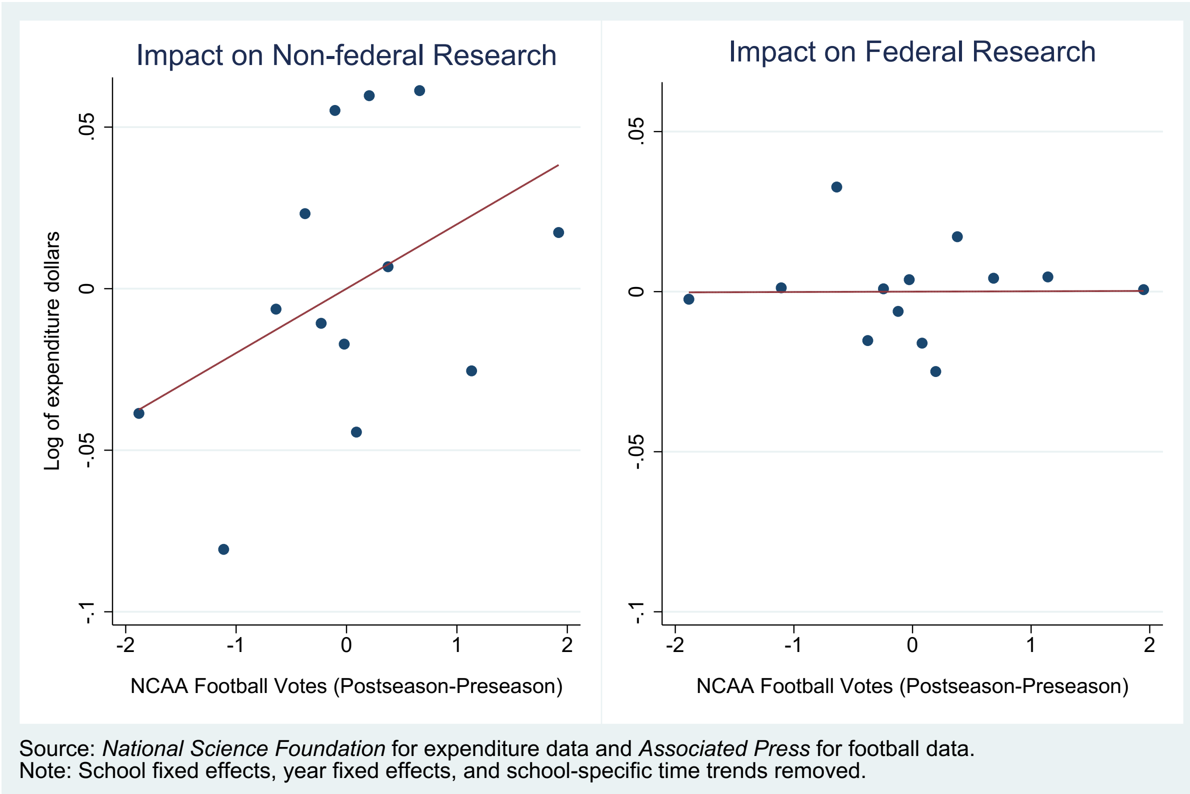

Figure 3.7: *Impact of football on federal vs. non-federal funding*

at over 99%. The second column shows analogous results when the log of total non-social science and engineering expenditures is used as the left-hand side variable.[31]

We interpret this as support for the instrument. As discussed in the Section 3.4, there are two potential problems with our identification strategy. The first occurs when unexpected football success causes success in the research or publication process—a direct violation of the exclusion restriction. The second occurs when a third, unobserved factor simultaneously drives football and research outcomes. For example, a new and charismatic college president could enhance both football and faculty recruiting. [32]

While both problems are *prima facie* unlikely to occur, Figure 3.7 lends additional proof.

[31]We thank James Lee for suggesting this specification.

[32]Our restriction to unanticipated football outcomes would further require that the star football recruits either go unnoticed by poll respondents in the pre-season poll, or join after the pre-season poll is completed.

Table 3.7: *Exogeneity check for instrument*

Dep. Var.:	Non-medical Non-social Science Expenditures	Non-social Science and Engineering Expenditures
	(1)	(2)
Non-Federal Dummy	35.24***	24.69***
	(0.0738)	(0.0679)
Instrument	0.000113	-0.000298
	(0.00383)	(0.00374)
(Non-Federal Dummy) x Instrument	0.0190***	0.0163**
	(0.00615)	(0.00672)
Constant	-23.12***	-11.64***
	(0.0517)	(0.0528)
School FE	x	x
Year FE	x	x
School Time Trend	x	x
R-squared	0.982	0.984
Observations	1,905	1,905
Number of Clusters	80	80

*Note: Standard errors, clustered at university level, in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.*

If the instrument causes, or is the result of, an aggregate productivity shock at the university-year level, then scientists could attract more grant money, which the data rejects. Moreover, if the instrument enables the university to recruit more productive faculty, or is the result of an unobserved factor that enables the university to recruit more productive faculty, then these new faculty members should bring a large influx of federal grant money with them. This, too, is rejected by the data.

3.5.7 Discussion of Timing

The empirical specification makes a strong assumption about a particular temporal relationship between football success, research funding, and scientific publishing. Misspecification of this relationship can result in biased estimates relative to the policy-relevant parameters.

Below we show that although the impact of football extends to periods other than what the model strictly specifies, the impact of funding does not. This leaves the estimates unbiased. Lastly, we discuss factors that drive this, seemingly compressed timing of the expenditures-publications relationship.

We first assess misspecification in the first stage. Our analysis assumes that football in period t mainly impacts funding in period $t+1$. However, football can impact funding at t if, for example, football inspires some immediate and directed donations to academic endeavors. It may also impact funding at $t+2$ and later if team success at the end of the season influences the starting point of success for future seasons. It should not, of course, impact funding at $t-1$, a period prior to the football season. Table 3.8 reports the relationship between funding and the seven prior years' instrument values as well as the current year and following year instrument values. A full set of controls are included. The first column reports the impact on the log of non-medical non-social science expenditures while the second reports the impact of the log of total non-social science and engineering expenditures. These results confirm our intuition about the first stage timing. In both cases, funding is most strongly impacted by one-year lagged instrument values and is not meaningfully impacted by the future value of the instrument. There is a non-trival impact from the instrument in the contemporaneous period and the instrument lagged more than one year. However, the coefficients tend to drop monotonically in terms of both magnitude and significance.

Expenditures, on the other hand, largely impact output in a single year, so the estimates are unbiased despite the impact of football being spread out. Table 3.9 reports this result for academic publishing. The left-hand side variable is the log of scholarly articles. The right-hand side variables are predicted values of leading, contemporaneous, and one- to three-year lagged research expenditures. In line with the model, the largest and only significant coefficient is on once-lagged expenditures. Table 3.10 reports the result for the case where the publishing measure is new patent applications. In line with the model once again, the largest and only significant coefficient is on contemporaenous year expenditures.

A one-year delay between research fund disbursement and subsequent publication of scholarly articles may strike readers as too fast, but several factors can explain this. In Section 3.4 we note that research budgets are reported on a fiscal year basis, while output is recorded on a calendar year basis, implying an added six month interval between funding and publishing periods. Also for projects facing funding bottlenecks, budgets will be spent soon after they are replenished. This results in the actual time lag we measure to be closer to two years rather than one. Futhermore, non-social non-medical scientific disciplines are anecdotally faster to produce tangible output than social science research. NSF grant data provides a direct evidence of this. For example, among all grants given out in 2000, 2005, and 2010, 26% resulted in the original grant year for physics-related proposals while only 5.4% of economics-related proposals did. Among grants over the same time period that resulted in at least one publication, 46% resulted in journal publications in the original grant year for physics-related proposals while only 13% of economics-related proposals did. The publication process is correspondingly fast. The receipt-to-acceptance time for manuscripts published in non-social non-medical science journals is around a third of those published in economics journals. For example, the average time between first submission and final publication was between 13 and 22 weeks at the five main journals of the American Physics Society[33] but 62 weeks at the *American Economic Review* (Moffitt [2009]).[34] Also, natural science disciplines in particular tend to rely more on short papers, proceedings, and letters, which have much shorter review times. For example, "rapid communication" section of the five main journals of the American Physics Society has an average receipt-to-acceptance time of between 9 and 15 weeks and a minimum of only two days.

The timing of patent filings is driven by different factors. To ensure intellectual property protection of an idea, scholars must submit their new patent application to the USPTO ahead of giving seminars or conference talks. On top of that, patents are generally faster to

[33]Dr. Thomas Pattard, "How to publish your work in the Physical Review (or Editors are from Mars, Referees are from Venus, and Authors are from Earth)" (presentation, International Max Planck Research School Summer Seminar, Dresden, Germany, August 11, 2011).

[34]This comparison is drawn from 2008.

write, and are assigned a "publication" date without a formal review process.[35]

Taken together, it is not surpring that the data indicates scientists file in the same period that research budgets are replenished. With respect to the timing of patent filings, our results are in line with earlier work in different settings. For example, in their study of manufacturing industry investments in R&D from 1972 to 1979, Hall et al. [1986] state that "R and D and patents appear to be dominated by a contemporaneous relationship."

3.6 Conclusion

Unanticipated within-season football success impacts school-sponsored research, providing rich exogenous variation that identifies the impact of money on science. An instrumental variable approach is important to study this relationship for two reasons. First, large grants are typically awarded to institutions that would otherwise attract big ideas, so any approach that ignores this endogeneity will recover upwardly biased parameters. Second, funding data include long-term projects with payoffs to researchers over many years, making it difficult to tie shifts in spending to shifts in scientific outcomes and creating an errors-in-variables problem that attenuates estimates toward zero. Our approach yields a dollar elasticity of scholarly articles at 0.31 and of article citations at 0.59. It also yields a dollar elasticity of new patent applications at 1.91 and of patent citations at 3.30. If citations are rough measure of quality, then these results suggest researchers are splitting their time between launching new projects and improving the quality of existing projects. We find it costs universities, at the margin, approximately $2.6 million to generate an idea worthy of filing a patent application. The inclusion of school specific controls, i.e. fixed effects and a school specific time trend, improved the first stage power but ultimately did not change the elasticity much for the 2SLS specifications. Their inclusion sharply reduced OLS estimates, which tended toward zero for all outcome measures. This highlights the importance of using instruments to "pick out" marginal expenditure shifts that can be tied to scientific

[35]While patents do not "publish" immediately, their priority date is locked when the application is submitted.

outcomes. Without them, this exercise would understate the returns to university R&D and lead policymakers to under-invest in research.

Table 3.8: *First stage timing*

Dep. Var.:	Non-Federal Non-Medical Non-Social Science Expenditures	Non-Federal Non-Social Science and Engineering Expenditures
	(1)	(2)
Instrument: 1 Year Ahead	0.00334	-0.00177
	(0.00729)	(0.00772)
Instrument: Contemporaneous	0.0206*	0.0115
	(0.0105)	(0.00756)
Instrument: 1 Year Prior	0.0316***	0.0242***
	(0.0113)	(0.00853)
Instrument: 2 Year Prior	0.0316**	0.0246**
	(0.0148)	(0.0108)
Instrument: 3 Year Prior	0.0328**	0.0227**
	(0.0128)	(0.0109)
Instrument: 4 Year Prior	0.0221	0.0132
	(0.0139)	(0.0129)
Instrument: 5 Year Prior	0.0213	0.00820
	(0.0129)	(0.0104)
Instrument: 6 Year Prior	0.0162	0.00554
	(0.0128)	(0.00892)
Instrument: 7 Year Prior	0.0116	0.00822
	(0.0144)	(0.0126)
Constant	7.831***	8.146***
	(0.0633)	(0.0626)
School FE	x	x
Year FE	x	x
School Time Trend	x	x
R-squared	0.977	0.984
Observations	673	673
Number of Clusters	40	40

*Note: Standard errors, clustered at university level, in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.*

Table 3.9: *Second stage timing: scholarly articles*

	(1)	(2)	(3)	(4)	(5)
1 Year Leading Expenditures	0.0204				
	(0.107)				
Contemporaneous Expenditures		-0.00767			
		(0.0976)			
1 Year Lagged Expenditures			0.310***		
			(0.117)		
2 Year Lagged Expenditures				-0.225	
				(0.249)	
3 Year Lagged Expenditures					-0.0297
					(0.176)
School FE	x	x	x	x	x
Year FE	x	x	x	x	x
School Time Trend	x	x	x	x	x
R-squared	0.993	0.993	0.989	0.990	0.994
Observations	949	909	869	829	789
Number of Clusters	40	40	40	40	41

*Note: Standard errors, clustered at university level, in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.*

Table 3.10: *Second stage timing: patents*

	(1)	(2)	(3)	(4)	(5)
1 Year Leading Expenditures	1.209				
	(1.999)				
Contemporaneous Expenditures		1.914**			
		(0.922)			
1 Year Lagged Expenditures			0.0623		
			(1.118)		
2 Year Lagged Expenditures				-1.448	
				(1.419)	
3 Year Lagged Expenditures					-0.558
					(1.649)
School FE	949	909	869	829	789
Year FE	0.993	0.993	0.989	0.990	0.994
School Time Trend	x	x	x	x	x
R-squared	0.892	0.851	0.911	0.867	0.904
Observations	609	607	607	607	607
Number of Clusters	39	39	39	39	39

*Note: Standard errors, clustered at university level, in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.*

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Appendix A

Appendix to Chapter 3

A.1 Allocating patent filings to universities

Identifying cohesive patent portfolios and patent applicants and assignees can be a difficult task. Numerous variations in names of patent-seeking institutions appear in USPTO records caused by either the variation in patent-prosecuting law firms or human errors and incorrectly spelled names. For example, there are 157 variations of assignee/applicant names grouped under the "University of California" umbrella in our Thomson Innovation patent sample. These names range from "*The Regents of the University of California*", "*University of California Berkeley*", "*University of California Los Angeles*", "*The Regents of the University of Caliofornia*", to the "*The Regents of the University of California*". In addition, to better identify university owned patents and patent applications, we utilize DWPI assignee classification available in Thomson Innovation: a unique 4-letter identifying code assigned to approximately 22,300 international patentees. For example, The University of California is assigned a unique 4-letter code "REGC", and in order to retrieve all patent records assigned to the University of California, we query Thomson database for all variations of assignee/applicant string grouped under "University of California" and associated with "REGC" assignee code for earliest patent priority years 1996-2011. It is important to note that, while we collect patent data starting with 1987, our panel officially starts in 1996. We start the panel in 1996 because of the effects that the international harmonization of the Unites States patent system in early 1990's had on university patenting behavior. As shown in Appendix Figure I, one of the patent law amendments with a significant impact was the introduction of provisional patent applications in June 1995.[1]

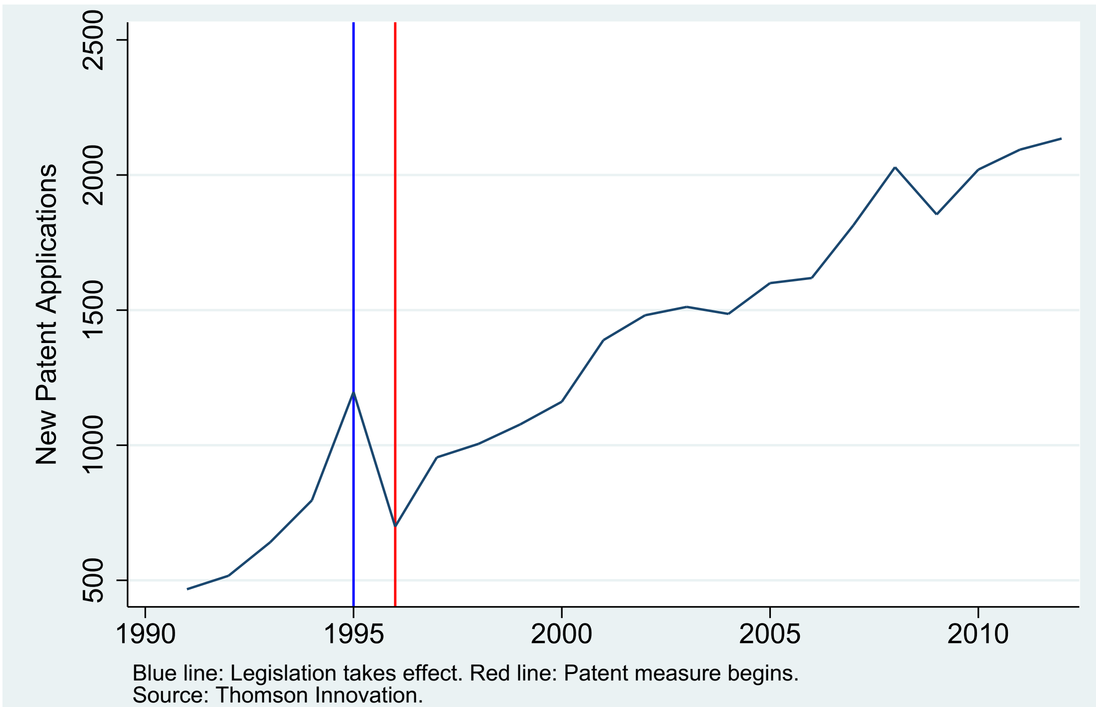

Figure A.1: *Patent applications filed over time*

Since the introduction of provisional patenting provided a convenient solution for academic researchers faced with publish-or-patent-first dilemma, it resulted in a sharp increase in university patent applications. A published article, a conference presentation, or even as much as a conversation describing an invention before a patent is filed represents a public disclosure, and can deem that invention unpatentable. To the extent that the scientific work in academia is first and foremost driven by article considerations in peer-reviewed

[1]As described in 35 U.S.C. §111, a provisional patent application allows an applicant to file an application with specification only, and without any formal patent claims, oath, declaration, or any prior art disclosures. A provisional patent application establishes an early patent filing date, but does not evolve into an granted patent unless the applicant converts it into a full patent application within twelve months. It effectively allows an applicant to lock-in a patent priority date, without being subjected to the cost of a regular patent application filing.

journals, provisional patent applications are an exceptionally good fit for this environment as they enable the university to lock an early priority date, while providing additional 12 months for inventors to publish, disseminate and improve the invention. Universities use provisional patent applications to reduce uncertainty surrounding market value of inventions and make a more informed decision of whether to prosecute full patents. Indeed, many university Technology Transfer Offices laud provisional patent applications as the first order of business after being informed of a new invention.[2]

Prevalence of provisional patenting in academia was the main reason behind our decision to stop our panel with patent applications filed in 2011. Since provisional patent applications take 12 months before they are published, patent application data from 2012 would be missing all provisional patents applied for in that year, and would result in a truncated patent count.

We use priority dates rather than application dates to count patent records because priority years most closely correspond with the date when the invention was *first applied for*. While the patent priority date is most often no different than the regular patent application date, in a case of a converted provisional application, a priority date will be earlier than the regular application date. This is especially the case when a divisional or a continuation application was filed. In addition, we use the DWPI Patent Family list available in Thomson Innovation database to assign all retrieved patent records to unique groups sharing the same priority application. This enables us to more closely identify patent groups surrounding the same invention and ensures that we do not overcount patent records in the sample. Each DWPI Patent Family is counted only once, and all forward patent citation counts are aggregated on a DWPI Patent Family level.

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[2]For example, see Office of Vice President for Research at Penn State http://www.research.psu.edu/patents/protect-your-invention/what-happens-after-submission), Innovation and New Ventures Office at Northwestern University (http://www.invo.northwestern.edu/process/assessment-patents), Northeastern University Center for Research Innovation (http://www.northeastern.edu/research/cri/inventors/commercialization-process/), or Boston University Technology Development (http://www.bu.edu/otd/for-researchers/technology-transfer-process/patentapp/).

A.1.1 Disaggregating state educational systems

To further exacerbate the problem of allocating patent applications to universities, some university systems do not specify campus locations where the invention was made when filing their patents. For example, almost 75% of all patent applications from University of California System in our sample are assigned to "The Regents of The University of California" without any additional information about invention-originating campus. Consequently, we do not know if the invention was made at The University of California at Berkeley, The University of California at Los Angeles, or any other campus in the system. Since our instrument works on the individual campus level only, and does not propagate through the whole system, we need to allocate patent applications to individual campuses within the university. In other words, unexpected success of The University of California at Berkeley football team will not impact R&D expenditures at The University of California at Los Angeles, and vice versa. To rectify this problem, we use the inventor's home address information provided on US patent records and use Google Maps API to calculate the "by car" estimated travel time from inventor's home address to every campus in the university system. We then systematically examine the patent portfolio and count a patent as originating at a specific university campus if at least one inventor lives less than 26 minute drive from that campus.[3]

A.2 A brief historical overview of college football

The strangely symbiotic relationship between football and national institutions of higher learning in the United States goes back for almost 200 years, all the way to football's early emergence from the English game of Rugby. Initial evolution, cultural assimilation and standardization of the game of football took place on campuses of colleges and universities

[3]This distance is based on the 2013 US Census American Community Survey estimate of mean travel time to work in the United States of 25.8 minutes. Our results are robust to different travel times: travel times of 15, 20 and 30 minutes did not cause any significant changes in our outcomes.

in Northeastern United States during the mid 19th and early 20th centuries.[4] From its inception, the sport was popular amongst students and alumni, while evoking much more of a mixed response from the faculty and administrators.[5] Because of the faculty indifference and disinterest during the football's early years, the games were organized and regulated mostly by athletes themselves, together with students and alumni. Largely due to the lack of adequate regulatory oversight, the early college football games were played without any protective gear, and players regularly sustained physical injuries. The apparent ferocity of the sport quickly garnered national attention, reaching all the way to the highest level of the national government.[6] In response to public concerns over player safety, university administrators formed Intercollegiate Athletic Association—a regulatory body which was renamed the National Collegiate Athletic Association (NCAA) in 1910. Initial role of the NCAA was limited to formulation of rules and creation of national championships for a variety of college sports, but as the outside interest in collegiate athletics grew and the commercialization pressures increased, the NCAA started to ramp up its governance activities. In the aftermath of World War II, as university enrollments exploded, so did the numbers of households owning radio boxes and television sets. The potential reach of college football and the commercialization pressures increased exponentially. Some universities like Notre Dame and the University of Pennsylvania embraced the advent of the new medium by crafting contracts with television networks on their own, while other schools remained cautious and expressed serious concerns that televised games would undermine their ticket sales [Dunnavant, 2004]. At this point, the NCAA stepped in and,

[4]The initiation of modern American football is widely regarded to have taken place on November 6th, 1869 when Princeton met Rutgers University for the first intercollegiate football game in history [Rudolph, 1962].

[5]While some saw it as a way to improve physical toughness, build leadership skills and unify student body, others saw it in direct conflict with essential values of higher education. In 1908, Harry Garfield, a president of Williams College remarked: "Here, as generally in American Colleges, there is a grave danger of departure from the essential idea of a college as distinguished from an institute of physical culture." [Rudolph, 1962]

[6]The season of 1905 was particularly brutal—eighteen students died playing football that year. At Harvard, every game but two produced player concussions. After a post-game photo of badly beaten, bloody and bruised face of Robert "Tiny" Maxwell, a Swarthmore College player was published in a newspaper, then-president Theodore Rusevelt made a demand for the colleges to eliminate the brutality and reduce injuries [Rudolph, 1962].

after comissioning a study of televised college football games and live attendance, imposed severe restrictions on televised broadcasts of college football games in 1953. For the next three decades, only one game was to be broadcast every Saturday, and no college team was to appear in a broadcast game more than once per season. These restrictions were finally lifted with the 1984 Supreme Court ruling that the NCAA violated antitrust laws by controlling television broadcasting rights. This decision ushered the college football into the modern era of unprecented popularity and profitability.