INNOVATION UNDER REGULATION: EXAMINING THE INTERPLAY OF REGULATION AND MARKET FORCES IN THE PATENT AND SPAC LANDSCAPES

by
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Submitted to the Graduate School of Social Sciences
in partial fulfilment of
the requirements for the degree of Doctor of Philosophy

Sabancı University
July 2024

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Date of Approval: July 23, 2024

ABSTRACT

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MANAGEMENT Ph.D DISSERTATION, July 2024

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Keywords: Regulation, Leahy-Smith America Invents Act, AIA, Patent Priority Rule, Patent Acquisition, Innovation, Mergers and Acquisitions, Special Purpose Acquisition Company (SPAC) IPOs

Regulatory interventions are often implemented to address inefficiencies and protect market participants. However, such policies can also generate unintended consequences, necessitating a thorough evaluation of their net impact. This thesis investigates the multifaceted impact of two distinct regulatory interventions regarding innovative technologies on their respective markets: the America Invents Act (AIA) of 2011, a landmark reform to the U.S. patent system, and the initial regulations regarding Special Purpose Acquisition Companies (SPACs), an innovative approach to traditional Initial Public Offerings (IPO), enacted in 2021.

The AIA, the most significant U.S. innovation market regulation since 1953, fundamentally altered the patent landscape, inducing a potential shift towards a market characterized by less cooperation and more competition. This thesis examines the impact of these changes on both the innovation acquisition market and the internal innovation market. Acknowledging the vital link between the merger and acquisition (M&A) market and innovation, Chapter 1 investigates the impact of the AIA's fundamental changes on innovation acquisition. Our findings reveal heightened activity in the innovation acquisition market, evidenced by a significant increase in the number of acquired patents, even when accounting for the overall changes in the

patenting landscape post-AIA. The observed surge in demand for innovation acquisition coincides with a decline in R&D investments and patenting activities among acquirers. Furthermore, acquirers of innovative targets decrease their innovative activities following the acquisition, suggesting a potential substitution relationship between the patenting market and the innovation acquisition market under the influence of post-AIA landscape. Notably, more significant innovation outputs attract multiple bidders, with longer deal completion times and significantly higher bid premia paid for these targets post-AIA, suggesting that the AIA's shift towards competition may be the primary culprit of the observed effects in the acquisition market. We also find some supply-side evidence where the number of firms available in the patenting market experiences a sharp decrease following AIA, potentially leading to supply-side constraints within the innovation acquisition market.

Chapter 2 further investigates the AIA's impact on the internal innovation market, analyzing its effect on the overall patenting landscape. Our findings reveal a decline in the growth rate of aggregate patent applications following the AIA, potentially jeopardizing future innovation. This decrease is further confirmed at the firm level, with a reduction in overall patenting activity by U.S. public firms and a decrease in the number of high-quality patents granted. The AIA's impact varies across firm sizes: smaller firms appear disproportionately affected, with some being pushed out of the market altogether. Smaller-to-medium sized firms, however, may have adapted by prioritizing quality over quantity, exhibiting a relative increase in high-quality patents compared to other size categories. Larger firms, on the other hand, show a trend of increased patenting activity coupled with a decrease in patent quality, potentially prioritizing quantity over quality to maintain market share. These findings highlight the complex and multifaceted impact of the AIA on the patenting market. The observed decline in patenting activity and quality necessitates further investigation to understand the potential long-term consequences for U.S. innovation and competitiveness.

In the last chapter, we investigate the effect of the first regulatory event in the scope of Special Purpose Acquisition Companies (SPACs) in 2021, a financial innovation which is an alternative way of taking firms public. In that sense, it is considered to be an alternative to the conventional Initial Public Offerings (IPOs). Since SPACs were initially perceived as benefiting from a regulatory gap, this study investigates whether the initial regulatory intervention resulted in negative market reactions for SPACs. Contrary to our initial hypothesis, the findings reveal no significant negative impact on SPAC performance following the SEC announcement. However, the analysis uncovers certain SPAC characteristics that negatively affect returns in a multivariate setting. Despite the regulations targeting warrant accounting, the study finds that offering warrants in SPAC units actually positively impacts announcement returns.

ÖZET

İNOVASYONU ŞEKİLLENDİREN DÜZENLEMELER: PATENT VE SPAC PİYASALARINDA ANALİZ

MERVE MERIÇ-YILMAZ

YÖNETİM BİLİMLERİ DOKTORA TEZİ, TEMMUZ 2024

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Anahtar Kelimeler: Düzenlemeler, Leahy-Smith America Invents Act, AIA, Patent Öncelik Kuralı, Patent Alımı, İnovasyon, Birleşme ve Satın Alma, Özel Amaçlı Halka Arz Şirketleri, Halka Arz

Düzenleyici müdahaleler genellikle piyasa verimsizlikleriyle mücadele etmek ve piyasa katılımcılarını korumak amacıyla uygulanır. Ancak bu tür politikalar istenmeyen sonuçlara da yol açabileceğinden, net etkilerinin kapsamlı bir şekilde değerlendirilmesi gerekmektedir. Bu tez, yenilikçi teknolojilerle ilgili olarak ABD düzenleyici makamları tarafından çıkarılan iki farklı düzenlemenin ilgili piyasalar üzerindeki etkilerini incelemektedir.

İncelenen ilk düzenleme, 1953 yılından bu yana ABD inovasyon piyasasının en önemli düzenlemesi olarak kabul edilen 2011 tarihli Amerika Mucitler Yasası'dır (AIA). AIA, ABD kamu patent sisteminde önemli bir değişime yol açarak potansiyel olarak daha az işbirliğine ve daha fazla rekabete dayalı bir piyasa ortamı oluşturmuştur. Birleşme ve satın alma (M&A) piyasası ile inovasyon arasındaki önemli ilişkiyi dikkate alarak, ilk bölüm AIA'nın temel değişikliklerinin inovasyon edinimi üzerindeki etkisini araştırmaktadır. Bulgularımız, AIA sonrası dönemde inovasyon edinim faaliyetlerinde önemli bir artış olduğunu, bunun da satın alınan patent sayısındaki belirgin artışla kanıtlandığını göstermektedir. İnovatif hedef şirketlere yönelik talebin artması, bu şirketlerin satın alınması için daha uzun süreçlere ve daha yüksek satın alma primi ödenmesine neden olmuştur. Ayrıca, inovasyon edinimi yapan şirketlerin araştırma ve geliştirme (Ar-Ge) yatırımları ile patent faaliyet-

lerinde düşüş gözlemlenmiştir. Dahası, inovasyon odaklı hedef şirketler satın aldıktan sonra inovasyon faaliyetlerini azaltmaktadırlar; ki bu da patentlenme ile inovasyon satın alım piyasaları arasında potansiyel bir ikame ilişkisini göstermektedir. Yüksek patent sayıları olan şirketler birden fazla talibi çekmekte, bu şirketlerin satın alım işlem süreçleri uzatmakta ve bu hedefler için önemli ölçüde yüksek satın alma primi ödenmesine neden olmaktadır. Bu durum; AIA'nın rekabete dayalı yapısının, gözlemlenen satın alma piyasası etkilerinin temel nedeni olabileceğini düşündürmektedir. Ayrıca, patentlenme piyasasında inovatif firmaların sayısında keskin bir düşüş olduğu gözlemlenmiştir; ki bu da inovasyon satın alım piyasasında arz tarafında kısıtlamalara yol açabileceği ihtimalini akla getirmektedir.

İkinci bölümde AIA'nın inovasyon piyasası üzerindeki etkisi incelenmiştir. AIA, kapsamlılığı, somut değişiklikleri (ilk mülkiyet hakkı gibi) ve farklı katılımcı grupları üzerindeki eşsiz etkisiyle önceki reformlardan ayrılmaktadır. Bu çalışma, AIA'nın genel patentlenme ortamı üzerindeki etkisini inceleyerek önceki araştırmalara katkı sağlamaktadır. Bulgular, AIA sonrasında toplam patent başvuru sayısındaki büyüme oranında düşüş olduğunu, bunun da gelecekteki inovasyonu tehlikeye atabileceğini göstermektedir. Bu düşüş firma düzeyinde de patent faaliyetlerinde azalma ve yüksek kaliteli patent sayısında düşüş şeklinde kendini göstermektedir. AIA'nın etkisi firma büyüklüğüne göre de farklılık göstermektedir. Küçük firmalar orantısız şekilde etkilenmiş, bazıları tamamen piyasadan çıkmak zorunda kalmıştır. Orta büyüklükteki firmalar ise kaliteye odaklanarak hayatta kalmaya çalışmış, yüksek kaliteli patentlerde göreli artış göstermişlerdir. Büyük firmalar ise patent faaliyetlerinde artışa rağmen patent kalitesinde düşüş yaşamış, potansiyel olarak pazar payını korumak adına miktara öncelik vermişlerdir. Bu bulgular, AIA'nın patentlenme piyasası üzerindeki karmaşık ve çok yönlü etkisini ortaya koymaktadır. Patent faaliyetlerindeki ve kalitesindeki düşüşün ABD inovasyonu ve rekabet gücü üzerindeki potansiyel uzun dönemli sonuçlarının araştırılması gerekmektedir. Ayrıca, önemli patent politikası değişikliklerinde farklı katılımcılar üzerindeki potansiyel etkilerin göz önünde bulundurulması gerektiği vurgulanmaktadır.

Son bölümde, 2021 yılında geleneksel halka arzlara (IPO) alternatif olarak ortaya çıkan özel amaçlı halka arz şirketleri (SPAC'ler) ile ilgili ilk düzenleyici gelişmenin etkisi incelenmiştir. SPAC'lerin başlangıçta düzenleyici boşluktan faydalandığı düşünülmüşken, bu çalışma ilk düzenleyici müdahalenin SPAC'ler üzerinde olumsuz piyasa reaksiyonlarına yol açıp açmadığını araştırmaktadır. İlk hipotezimize aykırı olarak, bulgular SEC duyurusu sonrasında SPAC performansı üzerinde anlamlı olumsuz bir etki olmadığını göstermektedir. Ancak analiz, bazı SPAC özelliklerinin getirileri olumsuz etkilediğini ortaya koymuştur. Garanti haklarının muhasebesine yönelik düzenlemelere rağmen, SPAC birimlerinde garanti hakkı sunmanın duyuru getirilerini olumlu etkilediği bulunmuştur.

ACKNOWLEDGEMENTS

Prof. Şerif Aziz Şimşir and Prof. Evrim Akdoğu deserve my sincerest thanks for their exceptional mentorship. Their unwavering support, insightful feedback, and constant availability have been instrumental in the completion of this dissertation. I am particularly grateful to Prof. Evrim Akdoğu, who has become a role model for me. Her dedication to her field and her success as a woman are truly inspiring.

My sincere thanks also go to the members of my dissertation committee: Assoc. Prof. Uğur Çelikyurt, Prof. Eren İnci, Asst. Prof. Bünyamin Önal, and Asst. Prof. Han Nazmi Özsöylev, for their valuable contributions, time, and effort invested in my research. I am grateful to Asst. Prof. Emre Ekinci for his insightful feedback on my first chapter.

This journey would not have been possible without the unwavering support of my dear friends Betül, Öykü, İmra, Mustafa, and Bardia.

I am eternally grateful to my parents, my little sister Sude, and especially to my dearest sister, Serpil, for their unwavering support and calming presence throughout my journey. Their belief in me, particularly during moments of doubt, was invaluable.

Special thanks to Selim Seyit Yılmaz and Kerim Cihan Yılmaz, my brothers, for their invaluable technical assistance during the data collection process.

To my dearest husband, Alican, your unwavering support has been the foundation upon which this accomplishment rests. I am grateful for your belief in my choices, your presence in every moment, and the wonderful father you are to our baby. You are my family.

To my baby, Ege, a heartfelt thank you for the joy you bring to every day. Your boundless energy has been a constant source of inspiration, and your unwavering spirit reminds me of the perseverance needed for this journey. I am incredibly fortunate to have you by my side.

Dedication page
To Ege and Alican

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1.1 Introduction

Innovation plays a vital role for firms, serving as an indispensable driver in increasing their value (Belenzon, 2012; Bloom and Van Reenen, 2002; Hall et al., 2005; Pástor and Veronesi, 2009) as well as laying the groundwork for future firm performance, making it a fundamentally strategic investment. Firms' innovation policies are shaped by various firm-, industry-, and economy-wide forces as well as the regulatory environment. As the most comprehensive regulation since 1953, the 2011 America Invents Act (AIA) marks a point of a significant shift in the U.S. innovation landscape. The primary and arguably the most impactful part of this legislation was the change from the first-to-invent (FTI) rule to the first-inventor-to-file rule (FITF). FTI rule guarantees that, regardless of the filing order, the first inventor gets the patent, even if that means a lengthy application to grant period and a costly litigation process. In contrast, the FITF rule simply grants the patent to the one who files first. This landmark change sparked anticipation of both intended and unintended consequences by academics, practitioners, and policymakers alike.

Proponents of the FITF system argue that it would expedite the innovation process by shortening the grant times and incentivizing quicker patent applications (Scotchmer and Green, 1990). The increased number of patent applications would expand the public knowledge base, stimulating future innovation. However, critics argue that FITF would hinder early-stage information sharing among inventors (Huang et al., 2021), leading to a more uncertain environment before application. Unaware of their competitors' ongoing projects, inventors may be much more likely to invest in overlapping research and development (R&D) activities that are unlikely to secure a patent, ultimately leading to higher expected costs. Higher information asymmetry may also remove the early project "abandonment option" for innovators, often employed as a risk mitigation strategy in such cases (Huchzermeier and Loch, 2001;

McDonald and Siegel, 1986). Additionally, the FITF system, akin to "winner-take-all" contests, could intensify competition (Halac et al., 2017), which may then put firms with limited resources at a profound disadvantage or even push them out of the innovation market altogether (Abrams and Wagner, 2013; Lo and Sutthiphisal, 2009).

While the impact of the AIA on the patenting landscape is an important and developing area of research, it is not the sole perspective through which to examine how firms acquire innovation. Firms can obtain innovation through various ways. The more conventional, in-house approach involves channeling investments into R&D initiatives, thus generating patentable concepts that create a competitive advantage over their industry peers. An alternative path to obtaining patents quickly and externally is through mergers and acquisitions (M&A), i.e., by acquiring innovative firms endowed with the desired patent portfolio already in place. These two methods are intricately linked and can function as substitutes (Levine, 2017; Zhao, 2009) or complements (Bena and Li, 2014; Phillips and Zhdanov, 2013; Sevilir and Tian, 2023). This complex relationship between direct patenting and acquisition strategies suggests that focusing primarily on the AIA's impact on patent applications provides an incomplete picture. A comprehensive understanding necessitates a concomitant analysis of both the patent application process and the dynamics of the innovation acquisition market.

In this study, we fill this gap by investigating the effect of the AIA on innovative M&A activity and by examining whether the Act's influence extends beyond the direct patenting market. First, the AIA's emphasis on the shift to the FITF system may create uncertainties and alter the cost-benefit tradeoff of the patent application process for some companies (Halac et al., 2017; Huang et al., 2021), in which case these firms may prefer to obtain readily available patent portfolios through targeted acquisitions (Cortes et al., 2021), leading to a shift towards more innovative targets post-AIA.[1] Second, with internal innovation becoming more costly post-AIA, acquirers who strategically pivot towards external sources of innovation may simultaneously reduce their internal efforts either temporarily or perhaps as a longer-term strategic approach (Cortes et al., 2021), shifting the dynamic between the internal and external innovation paths. Third, as claimed by the opponents of the Act, the challenges of the AIA may not be uniform for all firms, where those with limited financial resources may be pushed out of not only the direct application market but also the innovation acquisition where firms with ample resources are more likely to succeed. Finally, the higher demand for external patents may translate into a much

[1] Figure 1.1 provides compelling initial evidence of a significant increase in the average number of acquired patents per deal within the M&A market following the 2011 enactment of the AIA.

more competitive M&A market for innovative firms.

We first investigate whether the innovation activity of the acquired firms differs before and after the enactment of the AIA in 2011 by employing difference-in-difference analyses. We utilize two measures of firm innovativeness as dependent variables: patent flow, measured by the number of recently granted patents, and patent stock, indicated by the cumulative total of patents owned. Our findings indicate that both the patent flow and the patent stock of target firms acquired post-AIA are significantly higher than those of the targets bought pre-AIA. This is consistent with our first conjecture that the shift from FTI to FITF will increase the expected costs of internal innovation and incentivize firms to acquire innovation externally by bidding for targets with extensive patent portfolios, ultimately materializing as a "race to acquire patents." Interestingly, our results also show a significant decrease in the number of patents of innovative firms that did not become targets post-AIA. This contrasts with the expectation of the USPTO and the Act's other proponents for higher innovation levels and a higher number of patented innovations to be publicly available after the shift to FITF.

Next, we investigate whether acquiring firms utilize external innovation to supplement their internal innovation efforts or to replace them. To be more precise, we focus specifically on the firms acquiring innovative targets and find that while bidding for targets with high patent numbers, they also reduce their internal innovation efforts. Our results here point to a possible substitution effect where the acquisition of external innovation replaces internal activities, especially following the implementation of the AIA. What is more, this effect is not transitory and persists for at least a year after the acquisition. This contrasts with prior research suggesting a more complementary role between internal and external innovation where innovative M&As are followed by higher, not lower, internal efforts pre-AIA (Li et al., 2019; Li and Wang, 2020; Sevilir and Tian, 2023). Results may, therefore, signify a more permanent shift towards external innovation becoming a potential substitute, rather than a complement, to internal efforts after the AIA.

Finally, we investigate whether the heightened demand for innovative acquisitions fosters a more competitive M&A market. We find supporting evidence based on all three proxies of competition we utilize. After the AIA, the innovative targets receive competing bids significantly more often both compared to the pre-AIA period and to their counterparts with no patents. This intensified competition is also reflected in the extended deal completion times as negotiations take longer under the AIA regime. More importantly, the premiums paid for innovative targets are significantly higher during this period. Interestingly, we do not see these patterns for innovative targets before 2011: They do not receive more bids or higher premiums than their non-innovative counterparts, perhaps due to the prevalence of direct patent applications over acquisitions of existing patent portfolios pre-AIA. This makes the observed significant effects pointing to a more competitive environment after the AIA even more striking.

Our findings so far present a rich and exciting picture of the AIA's impact, echoing both the anticipated benefits and unforeseen consequences highlighted by proponents and opponents. In line with USPTO predictions, the shift from FTI to FITF has shortened the time between the application-to-grant-time for patents from 35 months to 30 months. However, mirroring concerns raised by opponents of the AIA, this shift towards FITF has created a more competitive and less collaborative innovation environment. This has led to firms diverting their focus from internal innovation efforts towards external sources of innovation. The heightened competition has extended into the M&A market for innovative targets, stimulating a "race to acquire patents," particularly among firms with limited patent portfolios and R&D investments. This behavior can be interpreted as a strategic response by these firms to maintain their competitive edge in the face of a rapidly evolving landscape.

Our next set of tests aims to complete the loop and provide a more detailed picture of the firm profiles participating in the external and internal innovation markets post-AIA. First, we check the acquirer characteristics and find that the firms rushing to acquire patents externally are the bigger, more profitable firms with higher cash holdings. Second, we check the number of firms that apply for patents after the enactment of AIA and find that it drops sharply. This decline is particularly pronounced among smaller firms, suggesting they could be at a greater disadvantage in both internal and external innovation markets, potentially facing total exclusion from the innovation market. This also suggests that a diminished supply, i.e., the reduced pool of potential innovative targets, may have contributed to the heightened competition in the M&A market. More interestingly, however, larger firms are not immune to this shift. The critics of the Act suggest that the adverse effects of the changing priority rule will disproportionately affect the smaller firms with limited resources and that larger firms will be relatively better off (Abrams and Wagner, 2013; Case, 2013; Lerner et al., 2015). Instead, we find that a substantial number of larger firms also exited the direct patent application path and even more rushed to acquire patents externally, suggesting that the AIA increased the expected costs of internal innovation even for big firms with ample resources.

As a last step, we rule out other factors that may drive our results. First, we check whether the targeted innovative firms possess patents of higher quality. Concerns exist that the shift from FTI to FITF under the AIA incentivizes premature patent applications, potentially leading to less thoroughly developed inventions compared to the pre-AIA era (Vandenburg, 2013). This could lead firms to pursue acquisitions to secure high-quality patents that may be more difficult to develop internally post-AIA. While our analysis confirms the concerns to some extent, revealing a slight decline in overall patent quality following the AIA, the targeted firms are not necessarily those with a higher or lower level of quality. Second, we check whether the anti-patent troll laws employed by various states during 2013-2018 can affect our results. We run a couple of different tests to ensure that this is not a contributing factor. We also use falsification tests with a placebo event, different patent datasets, a balanced panel approach, and various other econometric robustness tests. Our primary results remain robust. Our study makes several contributions to the existing literature.

First, we enhance the understanding of the AIA's impact on the innovation market by focusing on a critical yet unexplored path; patent acquisitions through M&As. We show that the uncertainties introduced by the AIA (Halac et al., 2017; Huang et al., 2021) incentivized firms to increasingly pursue M&As, leading to a surge in demand for innovative targets. This increased demand fueled a "race to acquire patents," with firms willing to pay significantly higher premiums for firms with extensive patent portfolios. Second, we provide empirical evidence regarding the AIA's impact on firms' internal innovation activities. While the AIA's impact on the patenting market has been widely discussed (Case, 2013; Huang et al., 2021; Lerner et al., 2015; Rantanen et al., 2011; Vandenburg, 2013), empirical evidence about its overall effects has been incomplete. We fill this gap by showing that AIA led to a decline in overall patenting efforts and patent quality, as well as a reduction in the number of public firms, small and large alike, which apply for patents. Third, by demonstrating that firms strategically utilize the M&A market to navigate disruptions caused by external shocks in the patenting landscape, we provide direct evidence on the interplay between external and internal innovation acquisition (Cortes et al., 2021). While this link has been previously studied (Bena and Li, 2014; Denes et al., 2018; Levine, 2017; Phillips and Zhdanov, 2013; Sevilir and Tian, 2023), our investigation of this relationship in the aftermath of an external regulatory shock helps us establish a causal link between firms' innovation strategies and their M&A decisions.

This paper is organized as follows. Section 1.2 establishes the conceptual framework. It defines the America Invents Act (AIA) and outlines its theoretical and empirical predictions regarding the patenting market, its connection with M&A markets, and the hypotheses guiding our investigation. Section 1.3 describes the sample selection procedure, data sources, and presents descriptive statistics of the key variables. Section 1.4 focuses on the demand side of the market. It presents baseline evidence on the increased demand for innovative targets following the AIA enactment. Additionally, it explores the internal innovation activities and characteristics of acquirers targeting innovative firms compared to those acquiring non-innovative firms. Section 1.5 analyzes the supply side of the market, focusing on the potential changes in the availability of innovative targets and its effects on the heightened competition for innovation acquisition. Section 1.6 assesses the quality of innovation post-AIA, examining both internal innovation and acquired innovation. Section 1.7 presents additional analysis assessing the robustness of the findings. Section 1.8 concludes and offers potential avenues for future research.

1.2 Conceptual Framework, Literature Review, and Hypothesis Development

1.2.1 The America Invents Act (AIA): Enactment and Implementation

The America Invents Act (AIA), considered the most impactful change to the United States (U.S.) patent system since 1953, is a comprehensive piece of legislation that the U.S. Congress enacted on September 16, 2011. The stated objective of the AIA is to streamline and modernize the U.S. patent system and harmonize it with the patent system of the rest of the world. Although the U.S. enacted the law in 2011, the effective dates of its provisions were not uniform and spanned over two years.[2]

The AIA made several notable changes to the patent system in the U.S., the most significant of which was arguably the switch from the FTI to the FITF system for granting patents, whose effective date was March 2013. Under an FTI system, the patents are granted to the first entity to invent a new technology. In this system, even if a second firm files a patent application before the true inventor, the patent is given to the first inventor. Sometimes, the FTI system allows for joint patents where multiple parties can share ownership rights. In contrast, the FITF system prioritizes the patent application's filing date. Regardless of the invention date, the USPTO grants patents to the first entity to file formally.

[2]The effective dates of the provisions of the AIA are available at:
`https://www.uspto.gov/sites/default/files/aia_implementation/aia-effective-dates.pdf`

The shift in the priority rule aimed to address two key issues: firstly, to alleviate the substantial workload and costs incurred by the USPTO in determining the original inventor under the FTI regime, and secondly, to expedite the patent granting process. By reducing bureaucratic hurdles and speeding up patent issuance, the USPTO expected the number of patents available in the market to increase. This expanded pool of technological knowledge would enable more firms to leverage the publicly disclosed information into a higher number of future patents, thereby stimulating more innovation (The White House Archives, 2011).

While the transition from FTI to FITF seems to have achieved its primary goal by expediting grant times,[3] it has spurred significant debate among academics and industry professionals regarding the potential unintended consequences of the new regime. The following section explores theoretical arguments and empirical evidence about these potential drawbacks.

1.2.2 The Switch from FTI to FITF: Theory and Evidence

The academic debate on patent priority rules has been ongoing since the 1990s. While some contend that the transition to FITF could lead to an escalation in innovation, others assert the contrary, anticipating a decline in firms' internal innovation activities. Proponents of the FITF, such as Scotchmer and Green (1990), argue that the FITF rule is superior to FTI as it expedites the patent granting process, reveals new technologies to the public early, and allows firms to build upon the disclosed technical knowledge. Thus, the FITF system should lead to an increase in firms' internal innovation activities.

In contrast with this argument, Halac et al. (2017) argue that, under the FTI model, firms are more willing to reveal their work-in-progress inventions to the public as they know they will still be rewarded for their inventions even if another inventor files the same patent first. Higher disclosure and more information-sharing at early stages allow inventors to still learn from each other but also minimize costly duplicate efforts by identifying such scenarios at a much earlier stage, allowing firms to use their "abandonment option" if necessary.[4] Under FITF, the firms are incentivized

[3]The average grant times decreased from 35 to 30 months after the AIA in our dataset.

[4]The importance and the value of real options in project selection has long been established (Pindyck, 1988; McDonald and Siegel, 1986; Pindyck, 1993). These options, particularly the abandonment option, has been shown to have even higher value in the industries/projects with heavy R&D involvement (Berger et al., 1996; Huchzermeier and Loch, 2001; Schwartz, 2004) and under increased uncertainty (Akdoğu and MacKay, 2008; Pindyck, 1988).

to keep their early stages more private, leading to more unidentified duplicate effort cases and effectively removing the innovator's option to abandon early. Since, at least in some of these cases, the firm will fail to win the race and file first; the new system is expected to increase the expected costs of converting R&D investment into patented innovation. Consistent with the first part of this conjecture, Huang et al. (2021) find that switching to FITF reduced the US firms' innovation disclosures in their 10-K statements, suggesting that innovators became more private under the new system.

The opponents also point out that the pressure to file applications rapidly under the FITF increases the risk of losing a patent race for some firms which are unable to keep up with the heightened competition and increased speed of the resulting process, which arguably resembles a public "winner-take-all" contest (Halac et al., 2017). This heightened competition can discourage entry and distort performance, potentially reducing total effort in winner-take-all contests (Cason et al., 2010; Fang et al., 2020), especially when the effort invested cannot be recovered (Clark and Riis, 1998). Similarly, this may lead firms to forgo certain efforts in the innovation market due to the high expected costs and potential for wasted resources if they are not the first to file. Given the increased uncertainty in turning R&D efforts into granted patents, such firms face diminished ex-ante incentives to invest in the first place (Miyagiwa, 2015; Miyagiwa and Ohno, 2015; Shapiro, 1985), possibly leading to a decline in R&D spending and internal innovation activities.

Using Canada's transition from an FTI to a FITF system in 1989 as their experiment, Lo and Sutthiphisal (2009) and Abrams and Wagner (2013) find a significant decrease in patent grants to individual inventors and small businesses, highlighting the potential adverse effects of FITF on these particular groups. Subsequent studies in the U.S. following the 2011 America Invents Act exhibit similar concerns (Case, 2013; Lerner et al., 2015; Rantanen et al., 2011; Vandenburg, 2013), indicating a consistent trend of increased challenges for small inventors under the FITF regime. The central argument of these studies is that the FITF system incentivizes firms to rush to file patents or forces a "race to the patent office," leading to an unfair competitive landscape and disproportionately benefiting larger corporations with significant resources and established filing infrastructure.

1.2.3 Innovation Acquisition through M&As: Theory and Evidence

It is well-established that innovation is not achieved solely through internal means. A significant body of research suggests that companies outsource innovation by acquiring other companies to access their innovative capabilities (Aghion and Tirole, 1994). Researchers have extensively studied the relationship between mergers and acquisitions (M&A) and innovation, revealing their roles as substitutes and complements.

Using a game-theoretic model, Phillips and Zhdanov (2013) show that in a scenario with no acquisition activity (i.e., an inactive M&A market), Nash equilibria often lead to minimal innovation, emphasizing the complementary nature of this relationship. Similarly, Sevilir and Tian (2023) empirically demonstrate that acquirers of innovative targets exhibit a subsequent surge in their innovation output compared to their peers who fail in their acquisition attempts. While Sevilir and Tian (2023) and Phillips and Zhdanov (2013) show the effect of an active M&A market for innovation on firms' patent application decisions, Bena and Li (2014) show that a reverse effect also exists, that a firm's chance of participating in M&As improves with its level of innovation activity. More specifically, they find that firms with lower levels of R&D spending yet more extensive patent portfolios are more likely to be acquirers, while firms with higher levels of R&D spending but weaker patent portfolios are more likely to be targets.

In contrast to these studies, which emphasize the complementary relationship between innovation acquisition and direct patent applications, Levine (2017) highlights their roles as substitutes in obtaining patents. In his model, firms that do not possess internal growth options acquire the innovative projects held by other firms. In other words, companies utilize M&As to acquire new technologies or capabilities that they cannot, or choose not to, develop internally. In support of this conjecture, Zhao (2009) demonstrates that firms with lower levels of innovation are more likely to become acquirers. Moreover, non-innovative bidders are also more likely to complete innovative deals, potentially because they may feel the pressure to do so.

Several papers in this line of literature perform conditional analysis and investigate the drivers of value creation and deal characteristics of innovative firm acquisitions. Sevilir and Tian (2023) report positive cumulative abnormal returns and long-term stock performance for acquirers associated with innovation acquisition. On the target side, Wu and Chung (2019) and Kaufmann and Schiereck (2023) find higher acquisition premiums paid to targets with more significant innovation activity. Innovative targets also attract more unsolicited bids and multiple bidders compared to their non-innovative counterparts (Wu and Chung, 2019) and receive higher stock payments, given the challenges in accurately determining their true values (Celik et al., 2022).

1.2.4 Hypotheses

The AIA is a significant regulatory change likely to affect firms' innovation strategies. Since firms can undertake innovation activities broadly through two means: by acquiring innovative firms already holding patents or by undertaking in-house R&D projects (e.g., direct patent applications), the final effect of the AIA on innovation acquisition depends on the relative benefits and costs of the two channels.

The major change brought by the AIA is the switch from the FTI to the FITF system. As discussed in Section 1.2.2, the FITF patent system is likely to increase the ex-ante risks faced by the firms planning to enter the innovation race, resembling a public "winner-take-all" contest (Halac et al., 2017). Following the implementation of the AIA, the expected costs linked to internal innovation efforts increase significantly, particularly in scenarios where competitors are simultaneously developing similar technologies. This situation, exacerbated by a limited information-sharing environment, increases the likelihood of duplicate efforts, ultimately diminishing the probability of successfully obtaining a patent (Halac et al., 2017; Huang et al., 2021; Shapiro, 1985). Consequently, firms are disincentivized from entering the innovation race and opt to limit or, in some cases, abolish their internal efforts altogether.

In such circumstances, the AIA would incentivize firms to seek targets with patents in place, triggering a "race to acquire patents" (Cortes et al., 2021). Acquirers may strengthen their existing patent portfolios with those held by the target firms or may simply kill the patents owned by target firms to preserve their competitive advantage (Cunningham et al., 2021).[5] Therefore, we expect a rise in acquired innovation as firms prioritize acquiring already-developed or soon-to-be-developed innovation rather than engaging in costly internal R&D activities.

Hypothesis 1: The enactment of the AIA led to increased competition in the innovation market. The increased costs of internal innovation incentivized firms to outsource innovation through M&As. Consequently, acquirers targeted more innovative firms following the implementation of the Act.

Increased innovation acquisition after the Act, as outlined in Hypothesis 1, has impli-

[5] The due diligence process performed by the acquirers during the M&As allows them to obtain private information about target firms, including the status of their R&D projects. Therefore, acquirers may have exclusive information on target firms' in-progress patents, in addition to their existing patents.

cations for acquirers' internal innovation efforts as well. Since the primary purpose of acquiring innovative firms is to quickly obtain externally developed technology, which has become too costly to obtain directly, we expect acquirers to substitute their current internal innovation projects with those developed by other firms, i.e., targets (Cortes et al., 2021). Therefore, we expect acquirers of innovative targets to pause or abandon their internal projects in place, by applying for fewer patents and reducing their R&D expenditures after the Act.

If acquirers plan to substitute only their current project portfolio with those developed externally, the impact of AIA on the acquirers' internal innovation efforts would be transitory. However, if acquirers view the acquisition as a long-term commitment to outsourcing innovation and select targets accordingly, acquiring innovative targets would mean a permanent shift from an internal to an external innovation strategy. In this scenario, acquirers of innovative targets would decrease their internal innovation efforts well after the acquisition. An empirical investigation along these lines is critical because several studies in the literature, such as Ahuja and Katila (2001), Cefis and Marsili (2015), Li et al. (2019), Li and Wang (2020) and Sevilir and Tian (2023), find evidence consistent with the conjecture that acquirers boost their internal efforts after acquiring innovative target firms especially when the merging firms have overlapping technologies (Bena and Li, 2014). In other words, acquirers select targets that complement, not necessarily substitute, their innovation activities. Thus, whether the Act changed the motivations of acquiring firms for external innovation is an important empirical question to investigate.

<u>Hypothesis 2:</u> The firms that acquire innovative targets after the AIA decrease their short- and long-term internal innovation efforts.

The critics of the AIA argue that anticipated internal innovation costs may not increase uniformly for all firms. Instead, they posit that smaller firms could be disproportionately affected, experiencing a more pronounced increase in these costs than larger firms (Abrams and Wagner, 2013; Case, 2013; Lerner et al., 2015; Vandenburg, 2013). A similar disadvantage for small firms may occur in the more competitive innovation acquisition market. While the heightened internal innovation costs incentivize all firms to pursue external innovation through M&As, small firms with limited resources may again fall behind the competition against larger firms with stronger financial resources. Therefore, while we anticipate an increased demand for innovation acquisition across all firms, those with ample financial resources are more likely to capitalize on these external opportunities.

<u>Hypothesis 3:</u> The increased demand for innovative targets after the AIA is driven by acquirers with ample financial resources.

Assuming a fixed supply of innovative firms available for acquisition, at least in the short run, increased demand for external sources of innovation following the AIA would likely translate into heightened competition for innovative target firms as well. This phenomenon could manifest in several ways. First, we anticipate an upward trend in bidders competing for innovative targets through public bidding wars (Liu and Mulherin, 2018). Second, a surge in bidders might lead to lengthy deal negotiations, thereby extending the completion times for acquisitions involving innovative targets, making them more challenging to finalize (Luypaert and De Maeseneire, 2015). Third, the increased competition for innovative targets in the post-AIA era may affect acquirers' pricing of target firms. A higher premium may indicate a stronger willingness to pay, suggesting a greater demand for these targets (Bradley et al., 1988; Bulow and Klemperer, 1996; Capron and Shen, 2007; Eckbo, 2009).

Hypothesis 4: The enactment of the AIA is associated with a heightened competitive landscape in the M&A market for innovative targets, as evidenced by an increase in the incidence of challenged bids, extended completion times, and inflated bid premiums.

1.3 Sample Formation, Variable Construction, and Methodology

1.3.1 Sample Formation

Our sample includes all firms in the CRSP-Compustat database, excluding those classified as regulated (Standard Industrial Classification codes 4900-4999) and financial (SIC codes 6000-6999). To identify target and acquirer firms within our sample, we utilize the publicly available dataset provided by Ewens et al. (2019)[6], which supplements the dataset linking deal numbers to acquirer and target GVKEYs provided initially by Phillips and Zhdanov (2013) between 1996 and 2016. We capture firms' patenting activity using the DISCERN dataset from Arora et al. (2021), which covers the patents granted to Compustat-listed firms between 1980 and 2015.[7]

[6] The dataset is accessible through the GitHub repository: `https://github.com/michaelewens/SDC-to-Compustat-Mapping`

[7] The dataset is accessible through `https://zenodo.org/record/4320782`. Although other patent-level datasets are available, we select Arora et al. (2021)'s dataset because it considers additional data sources such as SDC, ORBIS, and 10-K SEC filings to account for changes in firms' ownership structures resulting from mergers and acquisitions. This is particularly important to our research as we directly examine the M&A market. However, we also conduct our baseline tests with alternative datasets and continue to find

The combined availability of these three datasets restricts the sample period of our study to the years 1996-2015. This selection process results in a final sample including 92,902 firm-year observations.

We draw our M&A sample by extracting deals from the Securities Data Company (SDC) Mergers and Acquisitions database. Our dataset is refined by the criteria established by Bena and Li (2014), focusing on completed deals that meet the following conditions: (i) the deal falls into the categories of "merger," "acquisition of assets," or "acquisition of a major interest," (ii) the acquiring company initially possesses less than a 50% stake in the target firm before the bidding process, (iii) the acquiring company intends to secure over 50% ownership of the target firm, (iv) the acquiring company ultimately achieves ownership of more than 90% of the target firm upon the completion of the deal, (v) neither the acquiring company nor the target firm belongs to the financial sector (SIC 6000–6999), (vi) depending on the specific analysis, the target company must be included in Compustat/CRSP data. To construct our control variables, we match publicly traded target companies in SDC and CRSP/Compustat by utilizing the dataset provided by Ewens et al. (2019). Additionally, we draw on the DISCERN dataset from Arora et al. (2021) to capture the patenting activity of these target companies. To avoid potential confounding effects during the transition period, we drop mergers announced in 2011 from our sample.

1.3.2 Measures of Firm Innovation

We measure firm innovation using two established concepts from the literature: patent flow and stock (Griliches et al., 1986). Patent flow represents the influx of new patents, providing insights into a firm's recent innovation activities. We measure patent flow as the annual count of patents granted to a firm for a given year (Patent Flow). Patent stock represents the total number of patents that a firm has accumulated throughout its existence. To assess patent stock, we utilize the perpetual inventory method with a 6% depreciation rate (Celik et al., 2022). This approach yields the cumulative stock of past innovations at the firm-year level (Patent Stock). These metrics serve as proxies for a firm's innovation output. Additionally, we include R&D intensity for specific tests to measure innovation input and calculate it as the ratio of a firm's R&D investments to its total assets (R&D Intensity).

similar results. These results are available in Section 1.7.1.

1.3.3 Empirical Methodology

In the most basic sense, acquiring innovation "externally" can be conceptualized as the procurement of patents through the acquisition of other firms' patents, rather than developing in-house. Therefore, to determine if firms have shifted to the acquisition market for innovation, we may simply observe whether there has been a change in the number of patents granted to targets following the America Invents Act. We test our first hypothesis regarding innovation acquisition using a difference-in-differences model estimated on firm-year panel data consisting of all observations from CRSP/Compustat. This approach is consistent with existing literature and complements the companion chapter, which explores the relationship between internal innovation and the regulation.

$$\begin{aligned} \text{Innovation}_{i,t} = \alpha &+ \beta_1 \text{ Target}_{i,t} \\ &+ \beta_2 \text{ Post-AIA}_t \\ &+ \beta_3 \text{ Target}_{i,t} \times \text{Post-AIA}_t \\ &+ \beta_k \sum Z_{i,k,t-1} + \alpha_{IND,i} + \epsilon_{i,t} \end{aligned} \tag{1.1}$$

The dependent variable, $Innovation_{i,t}$, captures firm-level innovation output and is proxied by one of the two variables discussed in the previous section: the number of patents granted to a firm (*Patent Flow*) and the accumulation of past patents of a firm (*Patent Stock*). The variable of particular interest in this model is the interaction term between $Target_{i,t}$, which equals one if the firm is acquired in year t and zero otherwise[8], and *Post-*AIA_t, which equals one if the year is after the enactment of AIA and zero otherwise. If the Act significantly affected innovation acquisition, the interaction term between the two variables should capture this dynamic.

To follow the effect of the Act on a yearly basis, we employ an alternative specification, where we substitute *Post-*AIA_t with individual year dummies. This approach allows us to capture the AIA-driven effects more granularly and display the evolution of innovation acquisition around the Act's enactment.

Control variables include a set of firm characteristics ($Z_{i,k,t-1}$) that affect firm-level innovation (Chemmanur and Tian, 2018; Sevilir and Tian, 2023). These include firm size, R&D intensity, return on assets, asset tangibility, market valuation, industry

[8] Public firms delist after they are acquired. Hence, Target takes on a value of one for the acquisition year only.

concentration, and market leverage. Additionally, we include industry-fixed effects ($\alpha_{IND,i}$) in the model.

The majority of the firms in our sample are not involved in innovation activities, leading to zero patents or R&D expenditure for most firm-year observations. Recent literature suggests that the conventional approach of estimating linear regressions using the log of one plus the variable of interest may lead to biased estimates, particularly when the distribution of the outcome variable has a disproportionally large mass at zero and is highly skewed. Log transformation of such variables can lead to biased estimates and significantly distort the economic and statistical significance of the estimated coefficients (Chen et al., 2023; Cohn et al., 2022). To address this problem, we employ negative binomial models for estimating Equation 1.1, which yields efficient estimates when the dependent variables are over-dispersed, such as those in our case (Wooldridge, 2010). We also estimate the conventional "log1plus" linear model for robustness and comparability with the existing literature.

To test Hypothesis 2, we replace *Target*, an indicator for target firms, with an *Acquirer of Innovative Target indicator* in Equation 1.1 and re-estimate the model. This variable takes a value of one for firms that acquired a target firm holding patent stock in the year preceding the acquisition announcement. The dependent variable, $Innovation_{i,t}$, proxies firm innovation in the short- and long-term using both innovation input and output measures: the number of patents granted to the firm in the year of acquisition (*Patent Flow*), patent stock accumulated by the firm until the year of acquisition (Patent Stock) and R&D intensity (*R&D Intensity*) in the year of the acquisition. Our model investigates whether the acquirers of innovative targets exhibit a more significant decrease in their post-acquisition internal innovative activities in the post-AIA era than those acquirers who acquired non-innovative targets. For that purpose, we empirically test this conjecture by re-estimating Equation 1.1 in the subsample of acquirer firms.

To capture the potential time lag between the decision to adjust internal innovation and its manifestation, we also examine the acquirers' innovation activities measured at year t+1 ($Innovation_{i,t}$). If the innovation acquisition decision executed by acquirers is part of a long-term strategy to substitute internal innovation with external innovation, acquirers should also reduce their internal innovation in the year following the acquisition. In this case, the interaction term between *post-AIA and acquirer of innovative target* indicator would attain a statistically significant coefficient when acquirer innovation is measured one year after innovation acquisition.

To test Hypothesis 3, we re-estimate Equation 1.1 by decomposing *Target* based on specific acquirer firm characteristics. This setup allows us to explore how specific acquirer characteristics influence the demand for innovative targets. We proxy the financial strength of the acquirer with three binary variables. *Targeted by Large Firm* takes the value of one if the acquirer's total assets exceed the median total asset of the U.S. public firms in our sample. Similarly, *Targeted by High ROA Firm* equals one if the acquirer's return on assets is above the median ROA for U.S. public firms. Finally, *Targeted by Cash Rich Firm* equals one if the acquirer's cash-to-total-assets ratio is higher than the median cash ratio for the U.S. public firms in our sample.

Finally, we estimate difference-in-differences regression models using deal-level data to test our fourth hypothesis regarding the competition for innovative targets in the takeover market.

$$\begin{aligned}
\text{Takeover Competition}_{i,t} = \alpha &+ \beta_1 \text{ Innovative Target}_{i,t-1} \\
&+ \beta_2 \text{ Post-AIA}_t \\
&+ \beta_3 \text{ Innovative Target}_{i,t-1} \times \text{Post-AIA}_t \\
&+ \beta_k \sum Z_{i,k,t-1} + \alpha_{IND,i} + \epsilon_{i,t}
\end{aligned} \tag{1.2a}$$

$$\begin{aligned}
\text{Bid Premium}_{i,m,t} = \alpha &+ \beta_1 \text{ Innovative Target}_{i,t-1} \\
&+ \beta_2 \text{ Post-AIA}_t \\
&+ \beta_3 \text{ Innovative Target}_{i,t-1} \times \text{Post-AIA}_t \\
&+ \beta_i \sum Z_{i,k,t-1} + \beta_m \sum Z_{i,m,t-1} + \beta_d \sum D_{i,d} \\
&+ \alpha_{IND,i} + \alpha_{IND,m} + \epsilon_{i,t}
\end{aligned} \tag{1.2b}$$

The dependent variable in Equation 1.2a, *Takeover Competition*$_{i,t}$, is proxied by two distinct variables. *Challenged Deal*$_{i,t}$, is a binary indicator taking a value of one if the target firm i receives multiple public bids in year t and zero otherwise. The second, *Completion Duration*$_{i,t}$, captures the days elapsed between the merger announcement and closing dates. Equation 1.2b uses *Bid Premium*$_{i,m,t}$, as an alternative proxy to capture the demand of innovative target firms. This variable is the logarithm of the bid premium paid by acquirer m for target firm i in year t. The premium is calculated relative to the target's stock price four weeks before the announcement date (Eckbo, 2009).

Due to the nature of the dependent variables, we use a logit model to predict the effect of the AIA on deal competition (*Challenged Deal*$_{i,t}$), and OLS models to predict the premiums paid to target firms (*Bid Premium*$_{i,m,t}$) and the deal completion duration (*Completion Duration*$_{i,t}$). As discussed earlier, the key variable of interest in this context is the interaction term between *Innovative Target*$_{i,t-1}$ and *Post-AIA*$_t$, which captures the impact of the AIA on the relationship between a target firm's innovative activities and the level of competition it attracts.

While predicting Challenged Deal and Completion Duration, we control for target firm characteristics ($Z_{i,k,t-1}$) and industry fixed effects ($\alpha_{IND,i}$). These target firm characteristics include firm size, market-to-book ratio, asset tangibility, cash holdings, return on assets, leverage, and R&D intensity, all demonstrated to predict contested bids (Kaufmann and Schiereck, 2023; Wu and Chung, 2019). We estimate all control variables before the deal announcement as of the fiscal year-end.

In estimating *Bid Premium*$_{i,m,t}$, we employ the control variables mentioned above for target firms and introduce additional controls to account for acquirer ($Z_{m,k,t}$) and deal characteristics ($D_{i,d}$). These additional controls include acquirer firm size, market-to-book ratio, R&D intensity, and deal-specific variables such as indicators for all-stock, all-cash, tender offer, friendly, horizontal deals, challenged deals, asset-relatedness, and percentage ownership post-merger (Bena and Li, 2014; Phillips and Zhdanov, 2013; Wu and Chung, 2019). We also include target ($\alpha_{IND,i}$) and acquirer ($\alpha_{IND,m}$) industry fixed effects in the model. In all models, we employ robust standard errors adjusted for heteroscedasticity to ensure the validity of our statistical inferences. Appendix A provides detailed definitions of the variables introduced in this section.

1.3.4 Summary Statistics

We summarize the changes in innovation acquisition around the enactment of the AIA in Table 1.1. The table reveals that the total number of patents acquired through M&As post-AIA increased nearly 2.5 times compared to its pre-AIA level. Specifically, the targeted firms were granted 1,549 patents in the deal announcement year before the AIA, which surged to 3,868 afterward. Similarly, the targets' total patent stock increased by 58% over the same period, rising from 26,995 to 42,449. More importantly, the increased number of acquired patents does not come from increased bids for innovative firms post-AIA. In fact, the number of deals involving public and innovative firms decreased from 256 to 181 after 2011. Therefore, when we look at the innovation acquisition on a per-deal basis, we see an even higher upswing: the number of patents acquired per deal (i.e., patents held by targets) increased from 3.09 to 9.74, and the patent stock surged from 53.78 to 106.92 after the AIA.

While acquiring firms demand greater external innovation, they decrease their internal R&D spending. The number of patents held by acquirers per deal increases from 23.76 to 38.83, yet acquirer R&D expenditure drops from 6.61% to 5.45% of total assets. The decrease in acquirer R&D spending suggests a substitution effect within the innovation landscape post-AIA.

Table 1.2 presents the summary statistics for deal, target, and acquirer characteristics concerning the level of target innovation. Targets are categorized as "innovative" if they have at least one patent granted the year before the deal announcement. Other target firms are in the non-innovative group. Panel A shows that the average bid premiums paid to target firms are consistently higher for innovative targets both pre- and post-AIA, aligning with the findings of Wu and Chung (2019). This gap widens post-AIA, where the average premiums, based on the target price one week before the announcement, increase from 45.5% to 48.3% for innovative targets, while it drops from 42.1% to 37.6% for non-innovative targets. The difference in bid premiums is slightly higher when we use the target price four weeks before the announcement, where the average premium rises from 48% to 53% for innovative targets and drops from 46.9% to 41.8% for non-innovative ones.

Panel B of Table 1.2 provides preliminary evidence of increased competition for deals involving innovative targets after the AIA. First, despite fewer deals post-AIA, those involving innovative targets are contested more often compared to pre-AIA and non-innovative counterparts. While the percentage of challenged deals for innovative targets increase from 2.9% to 7.7%, they decrease from 6.2% to 3.8% for non-innovative ones. Second, we observe a similar trend when considering the number of bidders involved in the deals; the average number of bidders for non-innovative targets decreases from 1.67 to 1.04, while it increases from 1.03 to 1.08 for innovative targets. The time to complete a deal also shows a contrasting pattern. The average completion time for innovative targets increases from 102.62 to 110.76 days, whereas it decreases slightly for non-innovative targets from 110.82 to 109.09 days. Finally, as a possible proxy for hostile deals, hence increased bidder competition (Hirshleifer and Titman, 1990), we also observe that the frequency of a tender offer made to an innovative target slightly increases post-AIA, whereas the converse is true for non-innovative targets. Our observations align partially with the findings of Wu and Chung (2019), who suggest that innovative firms are pursued by multiple bidders compared to their non-innovative counterparts. Our results on this difference post-AIA are especially remarkable since we do not see this pattern in the pre-AIA period in our sample, where innovative targets seem to face, on average, lower demand than their non-innovative counterparts.

Panels C and D present the target and acquirer characteristics based on deals involving innovative and non-innovative targets, pre- and post-AIA. Notably, target size in the post-AIA period increases, particularly for deals involving innovative targets. This trend may indicate a preference among acquirers for acquiring relatively larger targets with greater innovation potential. Since the average size of targets is generally small, this may suggest a tendency towards targeting more medium-sized innovators post-AIA, potentially marginalizing the smallest players in both the patenting and innovation acquisition arenas. Such a shift is consistent with the recent literature discussing the challenges faced by smaller innovators after the enactment of the AIA. Moreover, R&D expenditures for innovative targets show a significant increase post-AIA, while firms acquiring such targets exhibit a notable decrease in their R&D investments. These univariate findings support the hypothesis that acquirers may shift their innovation strategy following the AIA and move towards external acquisition of established R&D capacity through innovative targets rather than internal R&D expansion.

1.4 Empirical Results

Univariate results provide some preliminary evidence that deals involving innovative targets post-AIA are associated with a higher number of granted patents, higher incidences of contested bids, and increased bid premiums compared to the pre-AIA period. In this section, we employ a difference-in-differences framework to assess the causal impact of the AIA on these outcomes, isolating its effect from potential confounding factors.

1.4.1 Innovation Acquisition Market Post-AIA

We first examine the impact of the AIA on target firms' patenting activity by comparing the change in granted patents for target firms post-AIA to a control group of untargeted firms. Table 1.3 presents the regression output for the empirical model shown in Equation 1.1.

Our findings strongly support Hypothesis 1, which is that acquirers target more innovative firms after the AIA. This is evidenced by a significant increase in the total number of patents owned or recently obtained by target firms post-AIA. In Column (1), the coefficient of *Target*$\times$ *Post-AIA* is 0.694, indicating that target firms in the post-AIA period obtain *twice as many* patent grants compared to their non-target counterparts. Target firms not only have more recently granted patents, but they also hold higher patent stocks. In Column (2), where the dependent variable is *Patent Stock*, the interaction term attains a coefficient of 0.630, indicating that, after the AIA, target firms possess 87.76% more patents in their portfolios in the deal announcement year than those of non-target firms.

The coefficients of *Target* and *Post-AIA* provide a glimpse into the innovation market before and after the AIA. The positive coefficient for the *Target* in Column (2) is consistent with prior research documenting an increased likelihood of becoming a target for innovative firms (Bena and Li, 2014; Wu and Chung, 2019). A significant and negative coefficient for *Post-AIA* suggests a general decrease in the number of patents after the AIA for the non-targeted firms. This starkly contrasts with the USPTO expectation of a general increase in the number of publicly available patents due to a change from FTI to FITF system.

The model in Columns (3) and (4) replaces the *Post-AIA* indicator with yearly dummies. The coefficients for the interaction terms in these columns attain positive and statistically significant coefficients for each year after the AIA. This finding indicates that, compared to untargeted firms, the total number of patents granted or recently obtained by target firms is significantly higher each year following the AIA. However, the results show almost no statistically significant difference in innovation activity between targeted and untargeted firms in the pre-AIA years.

Columns (5) and (6) provide further robustness by replicating the results presented in the first two columns over a more restricted sample period. The restricted sample uses observations from the 2007-2015 period, which leads to a balanced pre- and post-intervention period. This approach allows us to examine whether our baseline results continue to hold when the post-AIA observations are compared against those coming from shortly before the enactment of the AIA. Both models demonstrate statistically significant positive coefficients on the interaction terms for *Patent Flow* and *Patent Stock*, suggesting that our baseline findings are robust to alternative selection of pre-event periods.

The coefficients of the control variables in Table 1.3 are consistent with those reported in Chemmanur and Tian (2018) and Sevilir and Tian (2023), confirming that larger and more profitable firms with lower leverage and higher R&D are associated with higher innovation output. Moreover, our results indicate that lower asset tangibility is associated with increased innovation output.

These findings, as a whole, paint a nuanced picture of the innovation landscape post-AIA. While the USPTO anticipated a post-AIA "*race to the patent office*," our findings suggest a shift. Firms facing AIA challenges, opt for a "*race to acquire patents*" through the acquisition of innovative targets. This may highlight a strategic change: acquiring innovation rather than filing a surge of patent applications, as the AIA proponents expected.

1.4.2 Acquiring Firms' Internal Innovation Post-AIA

This section examines the function of external innovation within the context of the AIA regime. Specifically, we investigate whether acquiring firms leverage external innovation to support their internal efforts or entirely replace their in-house activities with readily available market innovations. To be more precise, we focus particularly on acquirers who targeted innovative firms instead of those who acquired non-innovative ones.

Table 1.4 presents the results. The dependent variables vary across columns to include innovation input and output measures. The first three columns of Table 1.4 measure dependent variables at the time (t), corresponding to the year of the deal announcement. This is meant to capture the more immediate relationship between acquirers' external and internal innovation activities. On the other hand, the final three columns of Table 1.4 use the acquirers' innovation activities in the subsequent year (t+1) to determine whether the observed immediate effect is temporary or is still present one year later.

The interaction terms *Acquirer of Innovative Target* × *Post-AIA* in Columns (1) and (2) reveal a statistically significant negative effect. This finding strongly supports our second hypothesis that firms acquiring innovative targets experience a simultaneous decrease in their innovative activities compared to acquirers of non-innovative targets. Specifically, acquirers of innovative targets exhibit a 68.25% reduction in patent grants and a 69.35% reduction in patent stock in the year of the deal announcement. This effect remains negative and statistically significant in Columns (4) to (6), suggesting that it persists for at least a year after the acquisition and is not a temporary effect. Compared to acquirers of non-innovative targets, these firms experience an 83.36% decrease in R&D investments and a 60% reduction in patent grants.

The coefficients of other variables provide results that are consistent with existing literature. For example, some studies find that acquiring firms tend to exhibit a pattern of high innovation output, measured by patents, while simultaneously maintaining lower levels of R&D intensity (Bena and Li, 2014). The positive coefficients associated with the *Acquirer of Innovative Target* variable in the innovation output models and the negative coefficients for *Acquirer of Innovative Target* in the R&D intensity models are consistent with these findings. Others find that firms utilize external innovation in a complementary manner to fuel their follow-up internal innovation efforts (Sevilir and Tian, 2023). The positive coefficients for the *Acquirer of Innovative Target* variable also support this notion in our sample but only for the pre-AIA period. This effect appears to reverse following the AIA.

Instead of a complementary relationship, our findings here point to a substitution effect between the internal and external innovation markets post-AIA: the rising demand for external innovation coincides with a decrease in internal R&D investment, which is more pronounced for firms acquiring innovative targets. Results that persist for the year after the deal announcement further suggest a potentially permanent shift in innovation strategy and resource allocation post-AIA, with firms increasingly relying on external innovation obtained through acquiring innovative companies, not as a complement but as a substitute to their in-house R&D projects.

1.4.3 Characteristics of Innovative Firm Acquirers

This section examines the type of acquirers that bid for innovative targets after the AIA, focusing particularly on their financial resources. This allows us to test Hypothesis 3, which suggests that large firms with ample financial resources may have an advantage over small firms with limited resources in paying competitive bid premiums, which results from the rush to acquire innovative targets. As a proxy for the financial resources of the acquirers, we use three characteristics: *Firm size*, *Cash holdings*, and *Profitability*.

Our findings in Table 1.5 reveal that the targets acquired by financially strong firms exhibit significantly higher pre-deal innovation output. Specifically, targets acquired by large firms after the AIA have higher patent flow (by 91.93%) and patent stock (by 104.82%) compared to the average public firm in the US. The coefficient for *Targeted by Large Firm* is positive and significant, indicating that large firms acquire targets with higher innovation stock even pre-AIA. A significant positive coefficient for *Targeted by Large Firm* $\times$ *Post-AIA* indicates that this effect is more pronounced following the AIA. Similarly, targets acquired by profitable or cash-rich firms after the AIA exhibit significantly higher pre-deal innovative activity than the average publicly traded U.S. firm, as measured by patent flow (increases of 72.46% and 144.73%, respectively) and patent stock (increases of 90.21% and 131.64%, respectively).

These findings are consistent with Hypothesis 3, which claims that financially strong acquirers drive the increased demand for external innovation after the Act. While the enactment of the AIA likely increases ex-ante internal R&D costs for all firms, firms with ample financial resources can overcome this challenge by strategically utilizing M&As to acquire external innovation.

1.4.4 Competition for Innovative Targets in the M&A Market

In this section, we investigate whether the increased demand for external innovation translates into heightened competition for innovative targets by focusing on several well-established proxies for competition in takeover markets, such as contested bids (Bradley et al., 1988; Capron and Shen, 2007; Ruback, 1983), completion duration (Luypaert and De Maeseneire, 2015), and bid premiums (Eckbo, 2009). Based on our fourth hypothesis, a more competitive environment is expected to produce a higher incidence of challenged deals, a longer time between the announcement and completion of the transaction, as well as higher bid premiums paid for the innovative targets.

Table 1.6 presents the regression results of the empirical models shown in Equations 1.2a and 1.2b. Due to the dynamic nature of the M&A markets, we estimate both models between 2007 and 2015, which provides balanced and comparable pre- and post-AIA periods. However, our results remain when the entire sample period is used in model estimations.

Columns (1)-(2), (3)-(4), and (5)-(6) in Table 1.6 use *Challenged Deal*, *Completion Duration*, and *Bid Premium* as dependent variables, respectively. To capture the innovativeness of target firms, we create a dummy variable indicating whether the target has at least one patent granted in the year before the deal announcement (*Granted Target*). We use the log of the target's patent stock before the deal announcement as an alternative measure (*Log(patent stock)*). Odd (even) columns use *Granted Target* (*Log(patent stock)*) as the target innovativeness measure.

Column (1) indicates that following the enactment of the AIA, targets with at least one patent granted during the year before the announcement are four times more likely to receive multiple bids than those without any granted patents. Similarly, the estimates presented in Column (2) indicate that target firms with large patent stocks are more likely to receive multiple bids after the Act. As the interaction term *Post-AIA* $\times$ *Log(patent stock)* indicates, a 1% increase in a target's patent stock corresponds to a 75.77% increase in the probability of receiving multiple bids. The coefficients of the two interaction variables are all positive and statistically significant, suggesting that the competition among the acquirers for innovative targets increased after the Act.

Columns (3) and (4) examine the relationship between deal completion time and the target firm's pre-deal innovative activities. While the coefficient for the interaction term in Column (3) is not statistically significant, the coefficient for *Post-AIA* $\times$ *Log(patent stock)* in Column (4) is positive and statistically significant at 8.832, indicating that a 1% increase in the target's pre-deal patent stock is associated with an average of 8-day increase in the completion time for deals finalized in the post-AIA era. These findings provide some evidence that acquisitions involving innovative targets may take longer to complete after the AIA enactment. Heightened demand for these targets may drive this effect, potentially leading to lengthy negotiations as multiple bidders compete to secure the deal.

Finally, we analyze the bid premiums paid to target firms in M&A transactions. If competition for innovative targets is fiercer following the AIA, bidders could be forced to pay higher premiums to target firms. Column (5) in Table 1.6 indicates that, following the enactment of AIA, targets with at least one granted patent in the year before the deal announcement earn significantly higher bid premiums compared to their counterparts with no granted patents. The effect of the Act on bid premiums is both statistically and economically significant: the average bid premium increases by 16.77% for innovative targets after the Act. Similarly, the coefficient of the interaction term in Column (6) indicates that targets with patents in place receive higher bid premiums after the Act: a one percent increase in the innovation stock of target firms in the year preceding the deal announcement is associated with a 2.98% rise in the bid premiums in the post-AIA period, compared with the pre-AIA period.

The combined evidence in Table 1.6 supports our last hypothesis and paints a compelling picture of heightened demand for innovative targets post-AIA through a more competitive bidding environment, extended deal completion times, and higher acquisition prices. These findings complement the results in the preceding sections, where we document a tendency of acquirers to implement external innovation strategies. This trend may suggest a potential spillover effect, where the "*race to the patent* *office*" appears to manifest in the innovation acquisition market, transforming it into a "*race to acquire patents.*"

1.5 Supply of Innovative Targets

Our findings so far reveal a growing demand for acquiring external innovation as a substitute for internal innovation; however, the final equilibrium of the innovation acquisition market is not determined only by the acquirers' constraints. Supply-side dynamics also play a crucial role. While we assume a fixed supply of innovative firms, at least in the short run, a shrinking pool of available firms with substantial patent portfolios could exacerbate the effects of increased demand for innovative targets in the long run. This effect may be significant since the AIA directly impacts the patenting landscape, potentially incentivizing some firms to completely withdraw from the innovation market altogether (Abrams and Wagner, 2013; Case, 2013; Lo and Sutthiphisal, 2009). In addition, the increased entry barriers associated with the increased expected costs under the AIA might deter new firms from entering the innovation market, potentially limiting the supply of innovative target firms.

To assess the potential shifts in supply-side constraints within the innovation acquisition market, we investigate whether the AIA has spurred changes in the number of firms actively engaged in in-house patent production. Given that these firms are potential targets for acquisition, any regulatory shift influencing their participation in the patenting arena could subsequently affect their availability as targets in takeover markets.

Figure 1.2a, utilizing data from Kogan et al. (2017), depicts a time-series trend suggesting a decline in the number of publicly traded firms filing patents in the U.S. While this figure is informative, making conclusions from this graph alone might be misleading due to the changes in the overall number of publicly traded firms over time. The well-documented "U.S. listing gap" points to a decline in the number of public firms since 1996 (Doidge et al., 2017). We confirm this trend in our dataset in Figure 1.2b. The dotted line in the figure shows the total number of publicly traded US-based firms in our sample, while the solid line shows the same statistic using the World Bank's data.[9]

Given the simultaneous decline in the total number of public firms and the number of

[9] The data is available through `https://data.worldbank.org/`. To obtain the number of publicly traded firms within the United States, we follow Doidge et al. (2017) and utilize the CRSP-Compustat merged database, excluding firms with Standard Industrial Classification (SIC) codes of 6722, 6726, 6798, and 6799.

firms with patent applications over time, the fraction of public firms filing at least one patent each year may provide a clearer picture of their innovation activities. Figure 1.2c depicts the evolution of this rate over time. While an initial "*race to the patent office*" appears evident after the enactment of the AIA in 2011, a notable drop occurred when the FITF rule became effective in 2013.[10]

The pattern after 2011 may suggest firms' initial response to the Act: rushing to the USPTO under the existing FTI rule before transitioning to the FITF. The subsequent long-term decline may indicate innovative firms' mass exit from the patenting market, which is consistent with the concerns raised by the opponents of the AIA's priority rule change (Abrams and Wagner, 2013; Lo and Sutthiphisal, 2009). Our findings imply a reduction in public firms generating patents under the new AIA regime, potentially leading to a more concentrated market structure. This trend may raise concerns about potential negative impacts on competition and innovation in the long term (Aghion et al., 1999; Ahmad et al., 2020; Blundell et al., 1995).

Figure 1.2d further investigates the patent application rate by firm size, segregating the data for small and large public firms to assess whether the observed decline originates primarily from a specific size group. Small (large) innovative firms are those with total assets below (above) the median total assets of all firms listed in the CRSP & Compustat database that filed a patent application in a given year. Figure 1.2d shows that small and large firms exit the patenting market after the AIA. Although large firms appear to have exited the patenting market following the enactment of the AIA in 2011, small firms exhibit a surge in patent applications, potentially to be subject to the FTI rule prior to the system switch. However, once the FITF rule became effective in 2013, small firms exited the patenting market significantly faster than large firms.

The observed decline in patent application rates, particularly among small firms, may raise concerns about a post-AIA reduction in the pool of innovative acquisition targets. This trend could impact the innovation acquisition landscape by further intensifying the competition. To investigate whether the decline in innovative targets affects the competition in the takeover market, we conduct a multivariate analysis

[10] To further isolate the impact of the AIA on public firms' patent filings, we build an empirical model to predict patent application rate after controlling for macroeconomic factors like GDP, trade openness, and change in domestic credit Bhattacharya et al. (2017); Furman et al. (2002). Table A.1 in the Appendix presents the results of the analysis. The variable of interest, *Post-AIA (implementation)*, takes a value of one for observations after 2013, the effective year of the priority rule change. We also construct *Post-AIA (enactment)*, which captures whether the supply-side constraints changed after the enactment of the AIA in 2011. After controlling for the macroeconomic factors, the two post-AIA variables attain negative and statistically significant coefficients, suggesting that following the enactment of the AIA, patent application rates are significantly lower than their pre-AIA levels. These results continue to hold when alternative patent data sources, such as Arora et al. (2021) DISCERN Dataset and the Virginia Darden Dataset, are used to calculate firm-level patent application rates.

with bid premium as the dependent variable and industry-level innovation density as the key independent variable. We hypothesize that the innovative firms operating in industries with low innovation density, indicated by a low patent application rate, are more attractive to acquirers; hence, takeover competition and bid premiums paid for such targets would be higher than those operating in other industries.

Table 1.7 presents the results of a differences-in-differences analysis, comparing the bid premiums received by innovative targets in industries characterized by high innovation density with those received by innovative targets in industries with a limited presence of innovative firms. The models in Columns (1) to (3) utilize a measure of *Industry Innovation Density* by dividing the total number of firms that have applied for at least one patent in that industry by the overall number of firms in the industry. While this approach captures the concentration of innovative firms within an industry, it may be a relatively coarse proxy for the supply of potential innovative targets, assuming all firms listed in CRSP & Compustat as potential targets. As we know from the M&A literature, smaller firms are more likely to be targeted in M&A transactions (Betton et al., 2008). Thus, *Industry Innovation Density* constructed exclusively for smaller firms may capture the supply of innovative targets more precisely. To that end, we estimate *Industry Innovation Density* by dividing the total number of small firms that have applied for at least one patent by the total number of small firms in the industry. Small firms are those with total assets lower than the median total assets in our sample. The final three columns in Table 1.7 use this alternative measure of innovative firm concentration. As before, we proxy the level of target innovation using an indicator for targets granted at least one patent in the year preceding the deal announcement.

The significant negative coefficient for the interaction term in the first three columns reveals that targets operating in industries with lower innovation densities tend to receive higher bid premiums in takeover transactions. The interaction between the alternative measure and target indicator is still negative in the last three columns, reinforcing our findings that potential supply constraints lead to heightened competition in the innovation acquisition market.

1.6 The Quality of Acquired Innovation

While patent quantity is a standard measure of firm innovation in the literature, patent quality is another crucial factor influencing firms' future innovation capabilities. While our analysis demonstrates a significant increase in external innovation post-AIA, we have not yet examined the quality characteristics of these acquired innovations. Could heightened demand for quality patents drive the observed rise in acquired patents following the AIA? One criticism of the AIA, specifically due to the shift from the FTI to the FITF system, was a potential decline in patent quality due to the "*rush to file*" effect (Vandenburg, 2013). If this concern is true, firms might prioritize acquiring existing high-quality patents, anticipating a future scarcity of such assets in the post-AIA environment.

To assess whether the AIA has influenced the quality of externally acquired innovation, we re-estimate Equation 1.1, using two distinct measures of patent quality as the dependent variable. The first measure is forward patent citations, a widely accepted indicator of a patent's scientific influence and potential value (Hall et al., 2005; Nicholas, 2008). To address the potential truncation bias in patent citations (Hall et al., 2005), we capture patent quality using the median number of citations each firm's patents receive within a 5-year window following the grant (*5-year Citations*) (Higham et al., 2021). The second measure, proposed by Kogan et al. (2017) and denoted as KPSS, involves using the stock market's response to patent grants to indicate the patents' value. The underlying premise is that higher-value patents will result in a substantial positive reaction in the stock market when granted. The authors also show that their patent-level assessment of economic value (i.e., KPSS) demonstrates a robust and positive correlation with the forward citations received by the patents in subsequent periods. We capture patent value through the median anomalous stock market reaction to firm-level patent grants each year *(KPSS)*.[11]

Table 1.8 presents the results of the analysis examining patent quality trends following the enactment of the AIA. We employ negative binomial models for our estimations due to the count or count-like characteristics of the dependent variables. Our findings align with the expectation of a decline in overall patent quality. The negative and statistically significant coefficients associated with the *Post-AIA* variable provide evidence for a general decrease in patent quality in the post-AIA period.

The interaction term *Target* $\times$ *Post-AIA* exhibits statistically insignificant coefficients in most model specifications. When the sample period is restricted to the 2007-2015 period, the interaction term attains a negative and statistically significant coefficient when patent quality is proxied by the KPSS (i.e., Column (4)). This finding suggests that target firms' patent quality declines following the enactment

[11] We use the PatentsView database, accessible at `https://patentsview.org/`, to evaluate patent quality based on citations. We also employ the dataset provided by Kogan et al. (2017), available at `https://github.com/KPSS2017/`. Further details on matching patents and citations with the CRSP database are available in Kogan et al. (2017)'s online appendix.

of the AIA compared to those of non-target firms. However, it is not possible to draw sharp conclusions from this single finding as alternative models do not lead to the same conclusion.

In unreported analysis, we examine if the quality of patent portfolios explains other proxies for takeover competition, such as the incidence of challenged deals or deal completion duration. This investigation would be particularly relevant if bidding wars occur only for innovative targets with higher-quality patents. However, our results reveal that patent quality is an insignificant determinant of takeover competition, measured by challenged deals or the length of deal completion. Overall, the AIA seems to increase takeover competition for innovative targets holding more patents rather than for targets holding higher-quality patents.

1.7 Robustness

1.7.1 Alternative Data Sources

The papers in the innovation literature use alternative patent datasets to conduct their empirical analyses. One widely used dataset that is an alternative to DISCERN, is the one constructed by Kogan et al. (2017), which links patents to CRSP firms from 1920 to 2022. This patent-level dataset enables users to extract the number of patents applied for (or granted to) each firm, their citations, and alternative patent importance values. It is worth noting that publicly traded firm-level patent activities exhibit a high level of correlation across all publicly available datasets, with correlations exceeding 96%. Nevertheless, we replicate our baseline regressions using the patent data available in the Kogan et al. (2017) dataset.

As Table 1.8 shows, our main results are robust to the use of this alternative patent dataset. In particular, *Target* × *Post-AIA* in Panel A and *Post-AIA* × *Granted Target* and *Post-AIA* × *Log(patent stock)* in Panel B attain positive coefficients, similar to their counterparts in Tables 1.3 and 1.6. Overall, the tendency of acquirers to target innovative firms after the AIA and the increased competition for these targets are also visible in this alternative setting.

1.7.2 Anti-Troll Patent Laws

While the America Invents Act (AIA) is a major regulation that shaped the innovation landscape, other patent-market-related events during our sample period may confound our analysis. One such event is the enactment of anti-patent troll laws.

A patent troll is a non-practicing entity (NPE) specializing in acquiring patents from various entities or individuals, often in large quantities. Instead of using these patents for product development or innovation, their primary focus is on making a profit by suing other companies for allegedly infringing on these patents or by seeking licensing fees. The literature extensively demonstrates that patent trolls have adverse economic consequences on the companies they target and their technological peers, reducing the value of continuous innovation in the market (Chen et al., 2023). Despite these adverse effects on firms, no direct federal legislation combating patent trolls exists. However, several states implemented anti-troll laws between 2013 and 2018 to bridge this regulatory gap, which overlaps our sample period. These state-level regulations influence internal and external innovation dynamics (Dayani, 2023). To ensure the robustness of our findings and isolate them from the potential effects highlighted by Dayani (2023), we present a series of robustness analyses in Table 1.10.

States implemented anti-troll laws at different points in time. Hence, we incorporate state-fixed effects in our models to account for the variances across states due to anti-patent troll legislation. Furthermore, we take a more conservative approach, discard all legislation states from our sample, and rerun the baseline regressions within the subset of states lacking anti-troll laws.[12]

Columns (1) and (2) in Panel A of Table 1.10 replicate the empirical model in Table 1.3 with *state-fixed effects added*. The models in Columns (3) and (4) exclude observations from states with *anti-troll laws* while controlling for state-fixed effects. The coefficient of the interaction term *Target*$\times$ *Post-AIA* remains statistically significant across all columns, suggesting that our baseline results in Table 1.3 are robust to the presence of state-level legislation.

Panel B in Table 1.10 replicates the model shown in Table 1.6 using the abovementioned remedies. The significant coefficients on the interaction term *Post-AIA* $\times$ *Log(patent stock)* in Columns (1) to (3) as well as in Columns (4) to (6) demonstrate that our core findings on the increased competition for innovative targets are

[12]To access the timing of the anti-troll laws by state, refer to the Supplementary Materials section in Dayani (2023).

robust to the potential confounding effect of anti-troll laws.

1.7.3 Falsification Tests

We perform falsification tests to address the possibility that unobserved factors rather than the Act itself are driving the results (Angrist and Krueger, 1999). For that purpose, we create a random event date at least four years before the Act so that the sample period does not overlap with the actual pre-AIA window in our baseline regressions. We replicate our analyses on external innovation and M&A market competition for the acquisitions of innovative targets, using the placebo event date (September 26, 2002).

Panel A in Table 1.11 shows the replication of the analysis in Table 1.3 with the placebo event date. Columns (1) and (2) present the results for the entire sample, excluding the years the AIA is effective (1996-2010). Columns (3) and (4) present the results for the restricted sample over four years before and after the placebo date (1998-2006). The coefficient of *Target* × *Post-2002* loses statistical significance in all columns of Panel A.

Panel B of Table 1.11 replicates the analysis in Table 1.6 with the placebo event date. The coefficients on the interaction terms *Post-2002* × *Granted Target* and *Post-2002* × *Log(patent stock)* lose statistical significance. These falsification tests suggest that the enactment of the AIA drives the original findings in Tables 1.3 and 1.6 rather than other coincidental factors.

1.8 Conclusions and Implications for Further Research

This study investigates the impact of the 2011 America Invents Act (AIA), the most significant patent law reform in the U.S. since 1953, on the innovation acquisition market. While previous research focused primarily on the AIA's effects on the direct patenting market, this study acknowledges the crucial role of external innovation acquisition alongside internal R&D efforts.

While the AIA aimed to increase innovation output and foster a more information-sharing environment by speeding up the patent application process, our study provides a different picture. We show that the AIA produced a more competitive patenting environment with higher information asymmetry, uncertainty, and ultimately higher expected costs of internal innovation due to less information-sharing by the inventors and the rush to file first. As a result, the firms appeared to decrease their internal innovation output while rushing to the M&A market to buy ready-made patents externally as a substitute strategy. Increased competition is also reflected in the M&A market and led to multiple bidders, longer time spent before transaction completion, and much higher premiums paid for the targets with a higher number of granted patents. The AIA's impact also reshaped the innovation industry structure, where a substantial number of firms exited the patenting market altogether, small and large alike. Results also point to the small firms being squeezed out of both the internal and external innovation markets, but some of the large firms also being affected enough to change their strategies, from in-house production to external acquisition.

Our research acknowledges several limitations that present valuable opportunities for future exploration. First, while mergers and acquisitions represent a primary avenue for innovation acquisition (De Man and Duysters, 2005), other strategies such as licensing agreements, joint ventures, and strategic alliances also play a role. Examining how the AIA influences the broader spectrum of innovation acquisition strategies would provide a more comprehensive understanding. Second, this study exclusively focuses on the public firms. As private firms are acknowledged as significant contributors to overall U.S. innovation (Wu et al., 2016), extending the research to include their behavior in the post-AIA landscape would offer valuable insights into the complete picture. Lastly, it is crucial to capture the long-term effects of the AIA. However, extended data with more recent years, is required to determine whether the observed effects are merely short-term solutions or represent a more lasting strategy.

1.9 Tables and Figures

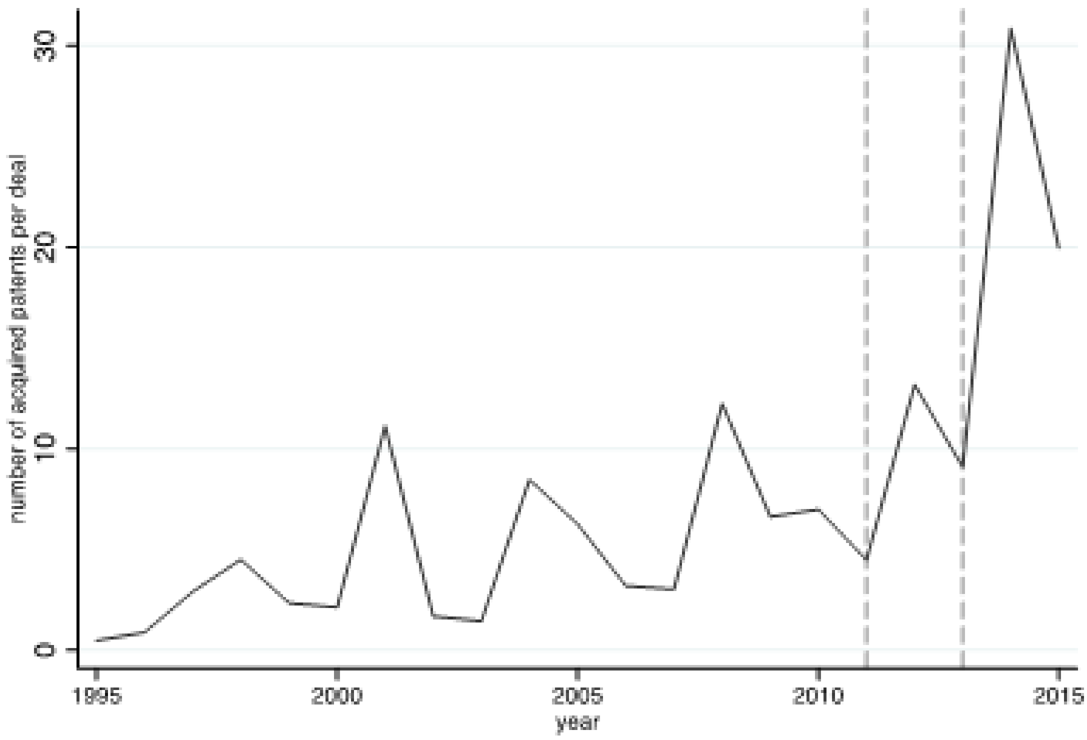
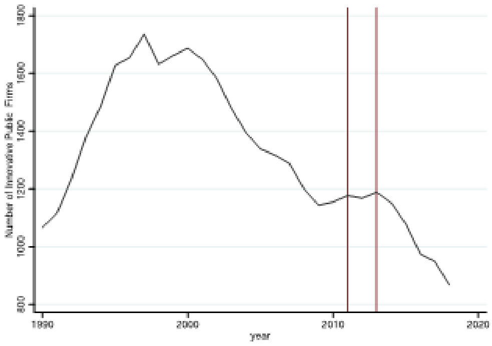
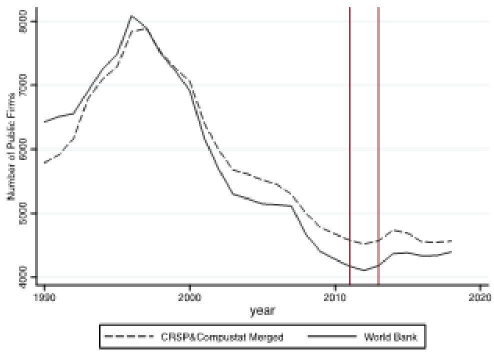


Figure 1.1 Acquired Patents per Deal

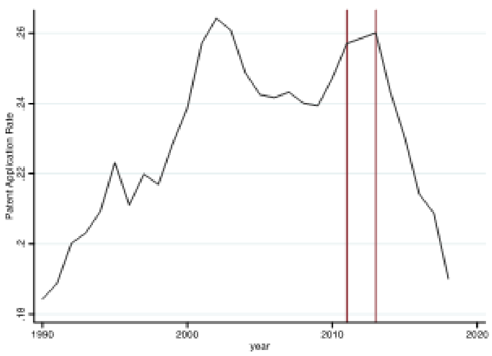
The average number of acquired patents per deal, calculated as the annual count of patents granted to targeted firms in the United States in the same year as the deal announcement, divided by the total number of deals. The vertical dotted lines mark the enactment of the America Invents Act (AIA) in 2011 and the implementation of the priority rule change in 2013.



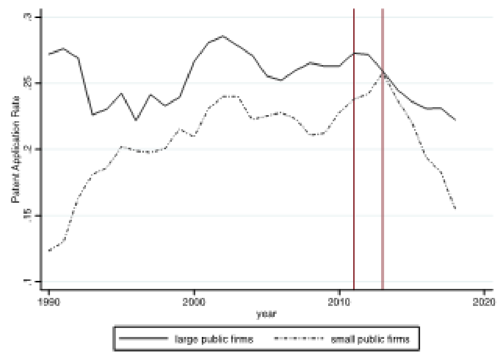
(a) Number of publicly traded (innovative) firms in the United States that filed at least one patent between 1990 and 2018, as sourced from Kogan et al. (2017). The red lines mark the enactment of the AIA in 2011 and the implementation of the priority rule change in 2013.



(b) Number of publicly traded firms in the United States between 1990 and 2018, sourced from the World Bank and CRSP-Compustat merged databases.



(c) Patent application rate for publicly traded firms between 1990 and 2018, as sourced from the Kogan et al. (2017) and CRSP-Compustat merged datasets.



(d) Patent application rate for small and large public firms between 1990 and 2018, as sourced from the Kogan et al. (2017) and CRSP-Compustat merged datasets.

Figure 1.2 Publicly traded U.S. firms and patent application pattern (1990-2018)

Table 1.1 Innovation Acquisition Market Characteristics: Pre-AIA versus Post-AIA

This table summarizes key characteristics of the Innovation Acquisition Market with respect to the pre-AIA (2007-2010) and the post-AIA periods (2012-2015). *Acquired patents* represent the total number of patents granted to target firms one year before their acquisition announcement. *Acquired patent stock* reflects the cumulative stock of patents owned by target firms in the year preceding the deal announcement, depreciated by 6% annually using the perpetual inventory method. *Acquired patents per deal* is calculated by dividing the total number of acquired patents by the total number of deals within each period. *Acquired patent stock per deal* is derived by dividing the total number of acquired patent stock by the total number of deals within each period. Public target deals refer to the number of deals where the target firm is public. *Innovative deals* represent the subset of public target deals where the target firm held at least one patent granted before the deal announcement. The final two rows depict the innovation characteristics of acquirers before the deals. *Acquirer patents per deal* represent the average number of patents granted to acquiring firms one year before the announcement. *Acquirer R&D intensity* reflects the mean ratio of R&D expenditures to total assets for acquirers, calculated one year before the deal announcement.

	Pre-AIA	*Post-AIA*
Acquired patents	1,549	3,868
Acquired patent stock	26,995	42,449
Acquired patents per deal	3.084	9.742
Acquired patent stock per deal	53.775	106.924
Public target deals	502	397
Innovative deals	256	181
Acquirer patents per deal	49.913	69.842
Acquirer R&D intensity	0.065	0.052

Table 1.2 Deal, Acquirer, and Target Characteristics

This table presents deal, acquirer, and target characteristics in our sample. We compare deals involving innovative and non-innovative targets before and after the AIA. The pre-AIA and post-AIA periods are 2007-2010 and 2012-2015, respectively. Innovative targets are those that are granted at least one patent in the year preceding the deal announcement, while the remaining are classified as non-innovative. The construction of variables is explained in Appendix A.

	Pre-AIA				**Post-AIA**			
	Innovative		Non-Innovative		Innovative		Non-Innovative	
	Mean	N	Mean	N	Mean	N	Mean	N
Panel A. Bid Premiums								
Bid Premium	0.480	132	0.469	222	0.530	100	0.418	196
Panel B. Deal Characteristics								
Challenged Deal	0.029	138	0.062	126	0.077	104	0.038	212
Number of Bidders	1.027	113	1.067	194	1.082	85	1.038	183
Completion Duration	102.62	138	110.18	242	110.76	104	109.09	212
All Stock	0.051	138	0.070	242	0.048	104	0.099	212
All Cash	0.746	138	0.678	242	0.692	104	0.599	212
Horizontal Deal	0.471	138	0.413	242	0.545	101	0.462	210
Tender Offer	0.384	138	0.302	242	0.413	104	0.274	212
Toehold	0.009	138	0.010	242	0.000	104	0.008	212
Asset Relatedness	0.594	138	0.710	241	0.683	104	0.689	212
Panel C. Acquirer Characteristics								
Size	8.723	107	8.612	152	8.896	81	8.429	140
R&D Intensity	0.067	138	0.027	242	0.054	104	0.020	212
ROA	0.125	107	0.143	152	0.152	81	0.119	140
Market Leverage	0.114	98	0.172	137	0.151	72	0.232	129
Tobin's Q	2.073	107	2.080	152	2.212	81	1.978	140
Panel D. Target Characteristics								
Size	5.819	138	5.427	242	6.331	104	5.742	212
R&D Intensity	0.145	138	0.081	242	0.153	104	0.085	212
ROA	-0.019	137	0.004	241	0.015	104	-0.005	212
Market Leverage	0.126	120	0.202	227	0.126	96	0.210	195
Tobin's Q	1.921	137	2.348	240	2.417	104	1.982	212

Table 1.3 Innovation Acquisition Around the AIA.

This table presents the regression results indicating the impact of AIA on innovation acquisition. Equation 1.1 is estimated using a negative binomial model. The dependent variables are *Patent Flow*, the number of patents granted to firms (yearly), and *Patent Stock*, the number of accumulated patents depreciated using the perpetual inventory method. The construction of the dependent variables is explained in Section 1.3.2. *Target* takes the value of one for firms acquired by another firm in the specified year and zero otherwise. *Post-AIA* is a binary variable that takes the value of one if the year falls after the enactment of the AIA in 2011 and zero otherwise. The first four columns present results for the full sample (1996-2015), with the final two presenting results for the restricted sample (2007-2015). Refer to Appendix A for detailed definitions of the control variables. All continuous variables are winsorized at their 1^{st} and 99^{th} percentiles. All specifications include industry-fixed effects. We employ robust standard errors adjusted for heteroscedasticity. t-values are enclosed in parentheses below the reported coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Patent Flow	*Patent Stock*	*Patent Flow*	*Patent Stock*	*Patent Flow*	*Patent Stock*
	(1)	(2)	(3)	(4)	(5)	(6)
Target	0.144	0.204***	-0.452	-0.119	0.245	0.304*
	(1.396)	(2.647)	(-1.117)	(-0.498)	(1.278)	(1.829)
Post-AIA	-0.16***	-0.065***			-0.034	-0.060***
	(-6.601)	(-3.534)			(-1.220)	(-2.826)
Target × *Post-AIA*	0.694***	0.630***			0.572**	0.488**
	(3.270)	(4.065)			(2.270)	(2.352)
Target × *1998*			0.208	0.070		
			(0.432)	(0.211)		
Target × *1999*			0.831*	0.404		
			(1.685)	(1.189)		
Target × *2000*			-0.329	-0.125		
			(-0.507)	(-0.321)		
Target × *2001*			0.701	0.525		
			(1.183)	(1.417)		
Target × *2002*			0.783	0.691		
			(0.850)	(1.622)		
Target × *2003*			0.546	0.223		
			(0.897)	(0.550)		
Target × *2004*			0.630	0.232		
			(1.093)	(0.626)		
Target × *2005*			0.675	0.539*		
			(1.306)	(1.737)		
Target × *2006*			1.521**	0.786		
			(2.421)	(1.257)		
Target × *2007*			0.309	-0.107		
			(0.551)	(-0.259)		

Table 1.3 – Continued from previous page

	Patent Flow (1)	*Patent Stock* (2)	*Patent Flow* (3)	*Patent Stock* (4)	*Patent Flow* (5)	*Patent Stock* (6)
Target × 2008			0.712	0.564		
			(1.056)	(1.210)		
Target × 2009			0.890*	0.774**		
			(1.755)	(2.431)		
Target × 2010			1.024*	0.667*		
			(1.897)	(1.684)		
Target × 2011			1.199**	0.738**		
			(2.546)	(2.403)		
Target × 2012			1.031*	0.944***		
			(1.842)	(3.152)		
Target × 2013			1.649***	1.153***		
			(3.426)	(3.370)		
Target × 2014			1.134**	0.905***		
			(2.247)	(2.650)		
Target × 2015			1.478***	0.968**		
			(2.731)	(2.540)		
Size	0.350***	0.196***	0.364***	0.190***	0.373***	0.188***
	(49.790)	(37.460)	(49.560)	(35.110)	(29.560)	(20.330)
R&D Intensity	2.727***	2.149***	2.712***	2.150***	2.975***	2.168***
	(34.740)	(34.840)	(34.390)	(34.920)	(21.650)	(19.870)
ROA	0.216***	0.342***	0.186***	0.365***	0.336***	0.398***
	(5.007)	(10.570)	(4.266)	(11.170)	(4.149)	(6.605)
Asset Tangibility	-0.80***	-0.648***	-0.92***	-0.619***	-1.42***	-0.943***
	(-10.940)	(-12.050)	(-12.300)	(-11.430)	(-9.931)	(-9.224)
Log(Market-to-Book)	0.128***	0.064***	0.128***	0.075***	0.153***	0.087***
	(12.660)	(8.169)	(12.210)	(9.245)	(8.537)	(6.302)
HHI	-0.125	0.037	-0.049	-0.096	-0.401	0.034
	(-0.472)	(0.186)	(-0.180)	(-0.471)	(-0.584)	(0.067)
HHI square	0.452*	0.463**	0.509*	0.508**	0.982*	0.324
	(1.735)	(2.346)	(1.940)	(2.544)	(1.695)	(0.712)
Market Leverage	-0.88***	-0.681***	-0.91***	-0.669***	-0.98***	-0.847***
	(-13.560)	(-14.370)	(-14.010)	(-14.050)	(-8.225)	(-9.762)
Constant	-0.86***	1.930***	-0.92***	1.858***	-0.301	2.219***
	(-3.020)	(9.297)	(-3.183)	(8.931)	(-0.594)	(5.397)
Sample Period		1996-2015			2007-2015	
Observations	65,886	65,886	65,886	65,886	23,328	23,328
Pseudo R^2	0.136	0.097	0.137	0.098	0.142	0.101

Table 1.4 Impact of the AIA on Acquirers' Internal Innovation Activities

This table presents the regression results examining the impact of the AIA on the internal innovation activities of acquiring firms. The dependent variables are *Patent Flow*, the number of patents granted to firms (yearly), and *Patent Stock*, the number of accumulated patents depreciated using the perpetual inventory method. *R&D Intensity* is the ratio of a firm's R&D expenditures to its total assets. The construction of the dependent variables is explained in Section 1.3.2. Because dependent variables are count/count-like, models are estimated using a negative binomial model. *Acquirer of Innovative Target* is a binary variable that takes a value of one if a firm acquired a target company possessing a patent portfolio before the deal announcement. *Post-AIA* takes a value of one if the year falls after the AIA's enactment in 2011 and zero otherwise. The first three columns capture the immediate response to the Act by measuring dependent variables at time t (the acquisition year). The last three columns examine post-acquisition innovation activity by measuring dependent variables at $t+1$ (one year after the acquisition). The sample period is 1996-2015 in all regressions. Appendix A provides detailed definitions of the control variables. All continuous variables are winsorized at their 1st and 99th percentiles. All specifications include industry-fixed effects. We employ robust standard errors adjusted for heteroscedasticity. t-values are enclosed in parentheses below the reported coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Patent $Flow_t$	*Patent* $Stock_t$	*R&D* $Intensity_t$	*Patent* $Flow_{t+1}$	*Patent* $Stock_{t+1}$	*R&D* $Intensity_{t+1}$
	(1)	(2)	(3)	(4)	(5)	(6)
Acquirer of Innovative Target	0.213***	0.191***	0.001	0.216***	0.203***	0.133**
	(3.114)	(2.987)	(0.023)	(2.956)	(2.991)	(2.216)
Post-AIA	-0.101	-0.072	-0.207***	-0.071	-0.036	-0.069
	(-1.290)	(-1.006)	(-3.141)	(-0.737)	(-0.413)	(-1.030)
Acquirer of Innovative Target × *Post-AIA*	-0.382**	-0.366**	0.090	-0.501**	-0.511**	-0.182*
	(-1.960)	(-1.980)	(0.771)	(-1.982)	(-2.171)	(-1.743)
Size	0.446***	0.341***	-0.041***	0.467***	0.357***	-0.053***
	(18.460)	(16.900)	(-3.158)	(17.220)	(16.050)	(-4.204)
R&D Intensity	3.092***	2.414***		2.544***	1.874***	
	(9.469)	(8.279)		(7.397)	(6.132)	
ROA	-0.082	-0.088	-1.126***	-0.270	-0.186	-1.517***
	(-0.368)	(-0.451)	(-8.838)	(-1.036)	(-0.831)	(-11.29)

Table 1.4 – Continued from previous page

	Patent Flow$_t$	*Patent Stock*$_t$	*R&D Intensity*$_t$	*Patent Flow*$_{t+1}$	*Patent Stock*$_{t+1}$	*R&D Intensity*$_{t+1}$
	(1)	(2)	(3)	(4)	(5)	(6)
Asset Tangibility	-0.789***	-0.767***	-0.052	-0.582*	-0.641**	-0.057
	(-2.581)	(-2.959)	(-0.209)	(-1.709)	(-2.182)	(-0.250)
Log(Market-to-Book)	0.095**	0.048	0.065**	0.117***	0.073*	0.150***
	(2.383)	(1.382)	(2.288)	(2.697)	(1.889)	(5.514)
HHI	-0.174	-0.263	-2.285***	0.231	-0.145	-1.747**
	(-0.199)	(-0.349)	(-3.059)	(0.233)	(-0.175)	(-2.111)
HHI square	-0.009	0.297	2.600***	-0.498	-0.084	1.425
	(-0.010)	(0.389)	(2.896)	(-0.483)	(-0.097)	(1.231)
Market Leverage	-0.306	-0.471**	-1.497***	-0.297	-0.546***	-1.309***
	(-1.268)	(-2.260)	(-6.516)	(-1.321)	(-2.650)	(-7.705)
Constant	1.459***	3.892***	-2.478***	1.320***	3.954***	-2.300***
	(3.604)	(8.283)	(-5.645)	(3.478)	(10.65)	(-6.826)
Observations	3,903	3,903	3,903	3,544	3,544	3,544
Pseudo R^2	0.131	0.094	0.208	0.139	0.103	0.215

Table 1.5 Acquirer Characteristics and Innovation Acquisition

This table presents the regression analysis results examining the impact of acquirer characteristics for innovation acquisition around the AIA. The dependent variables are *Patent Flow*, the number of patents granted to firms (yearly), and *Patent Stock*, the number of accumulated patents depreciated using the perpetual inventory method. The construction of the dependent variables is explained in Section 1.3.2. Due to the count-like nature of dependent variables, models are calculated using a negative binomial model. *Targeted by Large (Small) Firm* takes the value of one if the firm is acquired by a large (small) firm with total assets exceeding (below) the median total assets value of the overall sample. *Targeted by High (Low) ROA Firm* takes the value of one if the firm is acquired by a firm with a return on assets above (below) the median ROA of the overall sample. *Targeted by Cash Rich (Poor) Firm* takes the value of one if the firm is acquired by a firm with a cash ratio that is higher (lower) than the median cash ratio in the sample. The sample period is 1996-2015 in all regressions. All regressions include firm-level control variables and industry-fixed effects. All continuous variables are winsorized at their 1^{st} and 99^{th} percentiles. We employ robust standard errors adjusted for heteroscedasticity. t-values are enclosed in parentheses below the reported coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Patent Flow	*Patent Stock*	*Patent Flow*	*Patent Stock*	*Patent Flow*	*Patent Stock*
	(1)	(2)	(3)	(4)	(5)	(6)
Post-AIA	-0.155***	-0.064***	-0.155***	-0.064***	-0.155***	-0.0637***
	(-6.268)	(-3.266)	(-6.273)	(-3.269)	(-6.274)	(-3.273)
Targeted by Large Firm	0.249*	0.307***				
	(1.718)	(2.774)				
Targeted by Large Firm × *Post-AIA*	0.652***	0.717***				
	(2.601)	(3.123)				
Targeted by Small Firm	-0.468	-0.024				
	(-1.065)	(-0.106)				
Targeted by Small Firm × *Post-AIA*	0.375	0.356				
	(0.437)	(0.981)				
Targeted by High ROA Firm			0.238	0.302**		
			(1.520)	(2.516)		
Targeted by High ROA Firm × *Post-AIA*			0.545**	0.643***		

Table 1.5 – Continued from previous page

	Patent Flow	*Patent Stock*	*Patent Flow*	*Patent Stock*	*Patent Flow*	*Patent Stock*
	(1)	(2)	(3)	(4)	(5)	(6)
			(2.083)	(2.629)		
Targeted by Low ROA Firm			0.056	0.186		
			(0.214)	(1.071)		
Targeted by Low ROA Firm × *Post-AIA*			0.852	0.642		
			(1.251)	(1.594)		
Targeted by Cash Rich Firm					0.044	0.088
					(0.243)	(0.682)
Targeted by Cash Rich Firm × *Post-AIA*					0.895***	0.840**
					(3.023)	(2.444)
Targeted by Cash Poor Firm					0.413**	0.535***
					(2.161)	(3.640)
Targeted by Cash Poor Firm × *Post-AIA*					0.210	0.372
					(0.528)	(1.472)
Constant	-1.342***	1.438***	-1.344***	1.437***	-1.347***	1.435***
	(-4.781)	(6.862)	(-4.788)	(6.858)	(-4.797)	(6.860)
Firm Level Controls as in Table 1.3	Yes	Yes	Yes	Yes	Yes	Yes
Observations	65,886	65,886	65,886	65,886	65,886	65,886
Pseudo R^2	0.146	0.103	0.146	0.103	0.146	0.103

Table 1.6 Takeover Competition for Innovation Acquisition

This table presents regression results examining the impact of the AIA on takeover competition for innovative target firms. The dependent variable in Columns (1) and (2) is Challenged Deal, which takes a value of one for targets that receive multiple public bids, and zero otherwise. In Columns (3) and (4), Completion Duration represents the number of days between deal announcement and completion. In Columns (5) and (6), Bid Premium is the logarithm of the ratio between the offer price and the target's share price four weeks before the deal announcement. As for control variables, Granted Target takes a value of one if the target obtained at least one patent in the year before the deal announcement at t-1 and zero otherwise. Log (patent stock) is the logarithm of the total innovation stock at t-1, calculated using the perpetual inventory method with a depreciation rate of 6%. Appendix A provides detailed definitions of the control variables. The sample period is 2007-2015 in all regressions. Continuous variables are adjusted by winsorizing at the 1^{st} and 99^{th} percentiles. All regressions include industry-fixed effects. We employ robust standard errors adjusted for heteroscedasticity. t-values are presented in parentheses below the coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Challenged Deal	*Challenged Deal*	*Completion Duration*	*Completion Duration*	*Bid Premium*	*Bid Premium*
	(1)	(2)	(3)	(4)	(5)	(6)
Post-AIA	-0.533	-0.696	-23.740**	-27.070**	-0.068	-0.053
	(-1.023)	(-1.313)	(-1.999)	(-2.308)	(-1.596)	(-1.282)
Granted Target	-0.909		-3.467		-0.070*	
	(-1.260)		(-0.312)		(-1.895)	
Post-AIA × *Granted Target*	1.624*		16.280		0.155**	
	(1.939)		(0.968)		(2.376)	
Log(patent stock)		-0.343		-2.766		-0.014
		(-1.581)		(-1.067)		(-1.330)
Post-AIA × *Log(patent stock)*		0.564**		8.832**		0.029**
		(2.476)		(2.426)		(2.073)
Size (target)	0.080	0.093	17.780***	18.060***	-0.017	-0.019
	(0.499)	(0.554)	(4.845)	(4.595)	(-1.311)	(-1.449)
R&D Intensity (target)	-1.000	-0.864	39.110	4.284	0.134	0.141
	(-0.435)	(-0.385)	(0.766)	(0.096)	(0.545)	(0.563)

Table 1.6 – Continued from previous page

	Challenged Deal	*Challenged Deal*	*Completion Duration*	*Completion Duration*	*Bid Premium*	*Bid Premium*
	(1)	(2)	(3)	(4)	(5)	(6)
ROA (target)	-0.031	-0.077	-16.780	-26.460	0.035	0.053
	(-0.023)	(-0.055)	(-0.592)	(-0.934)	(0.246)	(0.360)
Asset Tangibility	2.394*	2.282	32.210	34.290	-0.075	-0.061
(target)	(1.740)	(1.542)	(1.218)	(1.278)	(-0.662)	(-0.496)
Log(Market-to-Book)	-0.163	-0.211	-12.410***	-12.020***	-0.079**	-0.085**
(target)	(-0.511)	(-0.619)	(-2.792)	(-2.608)	(-2.361)	(-2.463)
Market Leverage	-1.491	-1.649	-5.363	-5.121	0.035	0.042
(target)	(-1.480)	(-1.519)	(-0.306)	(-0.286)	(0.213)	(0.243)
Cash (target)	1.270	1.415	-20.260	-15.880	0.121	0.130
	(1.158)	(1.195)	(-1.264)	(-1.008)	(1.441)	(1.522)
Size (acquirer)					0.016	0.015
					(1.520)	(1.408)
R&D Intensity (acquirer)					-0.806	-0.859
					(-1.617)	(-1.649)
Log (Market-to-Book)					0.049	0.051
(acquirer)					(1.604)	(1.630)
Challenged Deal					0.120	0.123
					(1.519)	(1.466)
All Cash					0.038	0.035
					(0.931)	(0.812)
All Stock					-0.010	-0.015
					(-0.152)	(-0.230)

Table 1.6 – Continued from previous page

	Challenged Deal	*Challenged Deal*	*Completion Duration*	*Completion Duration*	*Bid Premium*	*Bid Premium*
	(1)	(2)	(3)	(4)	(5)	(6)
Tender offer					0.055*	0.057
					(1.667)	(1.645)
Friendly Deal					0.591***	0.597***
					(7.712)	(7.575)
Horizontal Deal					0.025	0.020
					(0.704)	(0.565)
Asset Relatedness					-0.001	-0.005
					(-0.017)	(-0.116)
Percent Owned After					-0.161	-0.182
					(-0.263)	(-0.271)
Constant	-1.139	-1.336	2.984	8.597	4.643***	4.709***
	(-0.606)	(-0.734)	(0.139)	(0.405)	(7.323)	(6.812)
Model	Logit	Logit	OLS	OLS	OLS	OLS
Observations	501	435	606	581	382	366
R^2 / Pseudo R^2	0.107	0.116	0.278	0.312	0.279	0.273

Table 1.7 Industry Innovation Density and Bid Premium

This table presents the results for the effect of the potential supply of innovative targets on the takeover competition for innovation acquisition. The dependent variable in Columns (1) through (6) is the logarithm of takeover premiums, calculated as the ratio between the offer price and the target share price four weeks preceding the deal announcement. Columns (1) to (3) calculate the *Industry Innovation Density* by dividing the number of firms with at least one patent application in an industry-year pair by the total number of public firms in that year. In Columns (4) to (6), *Industry Innovation Density* is the ratio of small firms (defined as those with total assets below the median) that applied for at least one patent in an industry-year pair to the total number of small firms operating in that industry year. *Granted Target* takes the value of one if the target firm obtained at least one patent in the year preceding the deal announcement. The sample period is 1996-2015 in all regressions. Continuous variables are winsorized at their 1^{st} and 99^{th} percentiles. All regressions include industry-fixed effects. We employ robust standard errors adjusted for heteroscedasticity. t-values are presented in parentheses below the coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Bid Premium (1)	*Bid Premium* (2)	*Bid Premium* (3)	*Bid Premium* (4)	*Bid Premium* (5)	*Bid Premium* (6)
Industry Innovation Density (Target)	0.131***	0.159***	0.147**	0.176***	0.210***	0.204***
	(2.924)	(2.876)	(2.185)	(3.665)	(3.496)	(2.700)
Granted Target	0.072**	0.117***	0.113**	0.046	0.073*	0.077*
	(1.995)	(2.593)	(2.408)	(1.499)	(1.842)	(1.831)
Industry Innovation Density (Target) × *Granted Target*	-0.220***	-0.272***	-0.262**	-0.211**	-0.221**	-0.230*
	(-2.643)	(-2.742)	(-2.396)	(-2.387)	(-2.056)	(-1.896)
Constant	4.927***	4.441***	4.382***	4.927***	4.464***	4.381***
	(359.400)	(18.370)	(9.078)	(410.500)	(18.790)	(9.217)
Deal Level Controls	No	Yes	Yes	No	Yes	Yes
Firm Level Controls as in Table 1.6	No	No	Yes	No	No	Yes
Observations	2,219	827	503	2,219	827	503
R^2	0.004	0.062	0.138	0.006	0.064	0.139

Table 1.8 Patent Quality in Innovation Acquisitions

This table presents the results examining the quality of acquired innovation following the enactment of the AIA. The dependent variables in odd-numbered columns capture the economic value of patents, measured by the number of future citations received (*5-year Citations*). The even-numbered columns use KPSS values as an alternative measure of economic value (*KPSS*). Section 1.6 explains the construction of the dependent variables in detail. Since the dependent variables exhibit a count or count-like behavior, models are estimated using a negative binomial model. The first two columns present the results for the entire sample period (1996-2015), while the final two use the restricted sample period (2006-2015). All regressions control for firm-level factors, similar to those used in Table 1.3, and include industry-fixed effects. All continuous variables are winsorized at their 1^{st} and 99^{th} percentiles. We employ robust standard errors adjusted for heteroscedasticity. t-values are enclosed in parentheses below the reported coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	5-year Citations	*KPSS*	*5-year Citations*	*KPSS*
	(1)	(2)	(3)	(4)
Target	0.005	-0.012	-0.137	0.079
	(0.043)	(-0.084)	(-0.764)	(0.857)
Post-AIA	-0.073***	-0.367***	-0.025	-0.207***
	(-3.664)	(-14.43)	(-1.020)	(-6.950)
Target × *Post-AIA*	-0.003	-0.202	0.199	-0.279**
	(-0.018)	(-0.945)	(0.915)	(-2.217)
Constant	-0.274	-1.429***	1.896***	-1.512***
	(-0.295)	(-6.769)	(3.359)	(-6.503)
Sample Period	1996-2015	1996-2015	2007-2015	2007-2015
Firm Level Controls as in Table 1.3	Yes	Yes	Yes	Yes
Observations	12,206	15,583	5,261	5,530
Pseudo R^2	0.030	0.144	0.036	0.198

Table 1.9 Robustness: Alternative Patent Dataset

Panels A and B of this table replicate Tables 1.3 and 1.6 using the patent dataset provided by Kogan et al. (2017). For more details on the empirical model and variable definitions, please refer to Tables 1.3 and 1.6.

Panel A. Innovation Acquisition

	Patent Flow	*Patent Stock*	*Patent Flow*	*Patent Stock*
	(1)	(2)	(3)	(4)
Target	0.005	-0.012	-0.137	0.079
	(0.043)	(-0.084)	(-0.764)	(0.857)
Post-AIA	-0.073***	-0.367***	-0.025	-0.207***
	(-3.664)	(-14.43)	(-1.020)	(-6.950)
Target × *Post-AIA*	-0.003	-0.202	0.199	-0.279**
	(-0.018)	(-0.945)	(0.915)	(-2.217)
Constant	-0.274	-1.429***	1.896***	-1.512***
	(-0.295)	(-6.769)	(3.359)	(-6.503)
Sample Period	1996-2015	1996-2015	2007-2015	2007-2015
Firm Level Controls as in Table 1.3	Yes	Yes	Yes	Yes
Observations	12,206	15,583	5,261	5,530
Pseudo R^2	0.030	0.144	0.036	0.198

Table 1.9 – Continued from previous page

Panel B. Takeover Competition

	Challenged Deal	*Challenged Deal*	*Completion Duration*	*Completion Duration*	*Bid Premium*	*Bid Premium*
	(1)	(2)	(3)	(4)	(5)	(6)
Post-AIA	-0.401	-0.653	-26.510**	-27.110**	-0.062	-0.047
	(-0.808)	(-1.196)	(-2.251)	(-2.177)	(-1.433)	(-1.098)
Granted Target	-1.219		-17.390*		-0.060	
	(-1.447)		(-1.764)		(-1.605)	
Post-AIA × *Granted Target*	1.582*		26.190*		0.147**	
	(1.705)		(1.762)		(2.174)	
Log(patent stock)		-0.120		0.977		-0.019
		(-0.821)		(0.278)		(-1.627)
Post-AIA × *Log(patent stock)*		0.403**		6.071		0.024*
		(2.257)		(1.300)		(1.659)
Constant	-1.065	-1.160	7.004	9.330	4.630***	4.571***
	(-0.564)	(-0.662)	(0.365)	(0.405)	(7.124)	(7.204)
Firm Level Controls as in Table 1.6	Yes	Yes	Yes	Yes	Yes	Yes
Deal Level Controls as in Table 1.6	No	No	No	No	Yes	Yes
Observations	501	501	606	606	382	382
R^2 / Pseudo R^2	0.106	0.109	0.281	0.283	0.276	0.271

Table 1.10 Robustness: The Impact of Anti-Troll Legislation

This table presents robustness checks to assess the potential influence of anti-troll legislation on the paper's main findings. Panels A and B replicate the analysis in Tables 1.3 and 1.6, respectively, using two alternative approaches to address the confounding effect of anti-trust legislation. The first two (three) columns in Panel A (Panel B) include state-fixed effects to control for unobserved time-invariant state-level characteristics. The final two (three) columns in Panel A (Panel B) exclude observations from states with anti-troll legislation. All specifications include industry-fixed effects. We employ robust standard errors adjusted for heteroscedasticity. t-values are enclosed in parentheses below the reported coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Innovation Acquisition

	Patent Flow	*Patent Stock*	*Patent Flow*	*Patent Stock*
	(1)	(2)	(3)	(4)
Target	-0.011	0.024	0.033	0.060
	(-0.194)	(0.294)	(0.519)	(0.650)
Post-AIA	-0.056***	-0.042**	-0.046***	-0.034*
	(-4.727)	(-2.493)	(-3.563)	(-1.841)
Target x Post-AIA	0.492***	0.664***	0.527**	0.746***
	(2.754)	(2.907)	(2.461)	(2.749)
Constant	-1.457***	-2.082***	-1.471***	-2.070***
	(-13.690)	(-14.910)	(-13.130)	(-14.190)
State FEs	Yes	Yes	Yes	Yes
Firm Level Controls as in Table 1.3	Yes	Yes	Yes	Yes
Observations	57,780	57,780	47,600	47,600
Pseudo R^2	0.431	0.505	0.435	0.506

Panel B. Takeover Competition

	Challenged Deal	*Completion Duration*	*Bid Premium*	*Challenged Deal*	*Completion Duration*	*Bid Premium*
	(1)	(2)	(3)	(4)	(5)	(6)
Post-AIA	-0.734	-24.940**	-0.060	-1.062	-35.530***	-0.101*
	(-1.337)	(-2.454)	(-1.270)	(-1.538)	(-2.753)	(-1.768)
Log (patent stock)	-0.352*	-1.174	-0.009	-0.433*	-1.581	-0.008
	(-1.647)	(-0.435)	(-0.881)	(-1.710)	(-0.491)	(-0.698)
Post-AIA $\times$ *Log(patent stock)*	0.577***	8.019**	0.030**	0.667**	9.192***	0.032*
	(2.641)	(2.350)	(1.987)	(2.507)	(2.694)	(1.813)
Constant	-0.328	-32.700	4.145***	-0.145	11.860	4.336***
	(-0.180)	(-1.039)	(6.092)	(-0.053)	(0.220)	(7.196)
Firm Level Controls as in Table 1.6	Yes	Yes	Yes	Yes	Yes	Yes
Deal Level Controls as in Table 1.6	No	No	Yes	No	No	Yes
Observations	304	581	366	261	477	309
R^2/ Pseudo R^2	0.189	0.396	0.352	0.228	0.414	0.338

Table 1.11 Falsification Tests: Placebo Event Date

This table replicates the baseline analysis using a placebo event date (September 26, 2002). Panels A and Panel B replicate Tables 1.3 and 1.6, respectively. The first two columns in Panel A present the results for the full sample from 1996 to 2010 (post-2011 is the post-AIA period, hence is excluded from the sample period). The last two columns present the results for a restricted sample from 1998 to 2006, mimicking the four-year pre- and post-event windows used in the actual analysis. In Panel B, the sample period is from 1998 to 2006. *Post-2002* takes a value of one for the years after 2002 and zero otherwise. Firm-level controls in both panels are identical to those shown in Tables 1.3 and 1.6. All specifications include industry-fixed effects. We employ robust standard errors adjusted for heteroscedasticity. t-values are enclosed in parentheses below the reported coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Innovation Acquisition

	Patent Flow	*Patent Stock*	*Patent Flow*	*Patent Stock*
	(1)	(2)	(3)	(4)
Target	-0.098	0.035	-0.029	0.089
	(-0.616)	(0.291)	(-0.171)	(0.637)
Post-2002	-0.139***	0.114***	-0.066***	0.132***
	(-6.406)	(7.086)	(-2.606)	(6.911)
Target × *Post-2002*	0.371	0.250	0.446	0.280
	(1.547)	(1.401)	(1.476)	(1.259)
Constant	-1.650***	1.299***	-1.950***	1.190***
	(-4.698)	(4.841)	(-4.114)	(3.802)
Sample Period	1996-2015	1996-2015	2007-2015	2007-2015
Firm Controls as in Table 1.3	Yes	Yes	Yes	Yes
Observations	45,230	45,230	31,078	31,078
Pseudo R^2	0.142	0.100	0.143	0.101

Panel B. Takeover Competition

	Challenged Deal	*Challenged Deal*	*Completion Duration*	*Completion Duration*	*Bid Premium*	*Bid Premium*
	(1)	(2)	(3)	(4)	(5)	(6)
Post-2002	0.405	0.390	4.239	4.993	-0.059*	-0.070**
	(1.255)	(1.220)	(0.775)	(0.939)	(-1.732)	(-1.967)
Granted Target	0.013		3.986		-0.007	
	(0.031)		(0.604)		(-0.193)	
Post-2002 × *Granted Target*	-0.307		-1.537		0.006	
	(-0.428)		(-0.157)		(0.130)	
Log(patent stock)		-0.029		3.682		0.001
		(-0.240)		(1.390)		(0.028)
Post-2002 × *Log(patent stock)*		-0.010		-1.772		-0.001
		(-0.052)		(-0.523)		(-0.105)
Constant	-2.116*	-2.089*	36.46***	39.32***	4.770***	4.759***
	(-1.911)	(-1.854)	(2.889)	(3.057)	(15.340)	(15.390)
Firm Controls as in Table 1.6	Yes	Yes	Yes	Yes	Yes	Yes
Deal Controls as in Table 1.6	No	No	No	No	Yes	Yes
Observations	1064	1044	1159	1137	745	731
R^2/ Pseudo R^2	0.120	0.120	0.299	0.304	0.149	0.150

2. AIA and Internal Innovation: Structural Shifts and Size-Dependent Effects on Patenting Activity

2.1 Introduction

Innovation is an essential driver for economic development and a source of competitive edge for both enterprises and nations (Fagerberg and Srholec, 2008). The patenting activity is a primary measure for assessing the innovative output of either an enterprise or a nation. While the patenting process might not capture all innovative efforts —for instance, undisclosed trade secrets or design innovations— it provides a significant and comparatively quantifiable measure of inventive activity (Acs et al., 2002; Pavitt, 1982). The examination of the patent landscape is, therefore, of importance for both policymakers and stakeholders who aim to cultivate an ecosystem of innovation. Understanding the dynamics of this market enables the formulation of targeted strategies that can incentivize and facilitate the processes related to patenting activities. Additionally, effective regulation is instrumental in ensuring a robust patent market that balances the interests of inventors, businesses, and societal welfare.

The U.S. patent market has experienced several legislative shocks over time. These key events, while distinct in their specific aims, are united by a shared vision: to foster a vibrant innovation ecosystem within the U.S. They aim to create an environment that encourages invention, facilitates technology transfer, and aligns US patent law with international standards. The America Invents Act (AIA) of 2011, however, stands out as the most transformative change to the U.S. patent system since the landmark Patent Act of 1953 (Miyagiwa, 2015), which established the foundation for modern patent standards. This comprehensive overhaul introduced a first-inventor-to-file system, revised patent eligibility criteria, and implemented changes to post-grant review mechanisms. While intended to streamline and modernize the system, its impact has been uneven, leading to divergent patenting trends across different inventor groups. This suggests that the AIA may have potentially created unintended structural changes within the innovation market.

This chapter investigates the impact of the AIA on the internal innovation market and its diverse participants. Extending the analysis presented in our preceding chapter, which focused on the innovation M&A activity within public corporations, this chapter broadens the scope to assess the influence of the AIA on the innovation ecosystem at large. To that end, we first summarize the regulatory history of the innovation market and show that AIA stands out as the one with the most comprehensive content and the one producing an asymmetric impact on different firm types with a potential to alter the industry dynamics of the patent market. Afterwards, we focus on the different firm subsamples, such as public vs private and small vs large public firms, and report the changes in their patent application numbers, changes in the quality of their patents and the number of their breakthrough patents as well as the time taken to complete the application to grant process. The results as a whole complete the loop by showing why AIA is a special regulation in the innovation market and how the internal innovation of firms changed after the implementation of this regulation. We first analyze patent activity at the aggregate level, including both public and private firms, comparing patent applications and their growth rates in the U.S. before and after the enactment of the America Invents Act (AIA). Our findings reveal a decrease in the number of patent applications and a decline in the growth rate. This suggests that the patenting market may be entering a period of stagnation following the implementation of the AIA. This observation aligns with existing empirical literature, which has previously studied the impact of similar policy changes, such as the Canadian priority rule change, and found evidence of reduced innovation levels (Abrams and Wagner, 2013; Lo and Sutthiphisal, 2009).

Next, we analyze the patenting activity at the firm level. Due to data limitations, this analysis focuses specifically on public firms. Innovation measures include both the quantity of patenting activity, as measured by the number of patent applications at the firm level, and its quality, as assessed by the median quality of firms' patents and the number of high-quality and breakthrough patents produced. The results confirm the findings at the aggregate level, suggesting a drop in patent applications following the AIA. Furthermore, the results indicate a decline in the average quality of patents and the number of high-quality and breakthrough patents following the AIA, lending support to the concerns expressed by critics of the legislation (Vandenburg, 2013). While the findings demonstrate the successful achievement of the USPTO's objective of reducing the time required to obtain a patent and expediting the patenting process, as evidenced by the significant reduction in the number of days between application and grant dates, this accomplishment comes at the cost of a decrease in both patent applications and the quality of innovation.

Finally, we analyze the non-uniform impact of the AIA on firms of varying sizes. We observe a significant decrease in both the number of patent applications and the quality of these applications by small firms, indicating a potential exclusion from the patent system. This suggests that the AIA's stricter requirements may be disproportionately challenging for the smallest firms, hindering their ability to effectively protect their innovations. Small-to-medium sized firms also face a decrease in the number of applications; however, we observe an increase in the quality of their remaining applications. This suggests a strategic shift towards higher quality patents, perhaps as a survival strategy in the face of increased costs under the AIA. The largest firms demonstrate an increase in the number of applications, potentially driven by their greater resources and capacity to navigate the AIA's complexities. However, we find a decrease in the number of high-quality or breakthrough patents within this group. This may indicate a focus on securing a greater volume of patents, even if they are not necessarily of the highest quality, to maintain market dominance.

We contribute to the existing literature by focusing specifically on the impact of the AIA on innovation activity within large, publicly traded corporations, a segment of the innovation market often overlooked in previous studies. Unlike previous studies that have examined the broader impact on the innovation market (Case, 2013; Lerner et al., 2015; Rantanen et al., 2011; Vandenburg, 2013), encompassing individual inventors and firms of all sizes, we provide a targeted analysis of the AIA's influence solely on corporations in the U.S., which are much larger than the samples previous studies used. Additionally, our research offers a more nuanced understanding of the AIA's effects on innovation activity across different firm sizes, dividing firms into more rigorous categories than previous studies. This allows for a deeper understanding of the specific challenges and opportunities presented by the AIA for various participants driving innovation in the U.S.

This chapter is organized as follows. Section 2.2 outlines key legislative events within the U.S. innovation market that have impacted the environment for corporate innovation. It compares the AIA to other legislations, discussing its unique characteristics and potential implications for innovation policy. Section 2.3 outlines the data and methodology employed in the study, focusing on the internal innovation activities of U.S. corporations within the post-AIA era. Section 2.4 presents the empirical findings regarding changes in internal innovation patterns following the AIA's enactment. Section 2.5 conducts several robustness analyses. Section 2.6 concludes by summarizing key findings and discussing their implications.

2.2 The U.S. Patenting Market: Evolution and Impact of Legislations

2.2.1 Key Legislative Events in the U.S. Patent System

Since the early 1980s, the United States has implemented a series of legislative events aimed at strengthening patent law and fostering a vibrant patenting environment.[1] The first pivotal step in this direction was the implementation of the Federal Courts Improvement Act of 1982. This legislation consolidated all circuit courts with jurisdiction over patent cases into a single court, the Court of Appeals for the Federal Circuit (CAFC), with the goal of promoting uniformity in patent law nationwide. This is essential due to the national scope of patents, as inventors rely on consistency and predictability in the interpretation and enforcement of their patents. Moreover, CAFC judges specialize in patent law concepts such as patentability criteria, infringement analysis, and remedies for patent infringements. By developing expertise in these areas, they can make well-informed decisions that significantly influence the evolution of patent law. The court's jurisdiction, specialized judges, and precedential rulings play a critical role in ensuring coherence, quality, and predictability within the US patent system.

While Congressional intent behind the CAFC aimed to establish consistency within patent litigation, some scholars have argued that the court's rulings have exhibited a pro-patent bias (Belenzon and Patacconi, 2013; Mazzoleni and Nelson, 1998; Merges, 1992). This argument stems from observations of the CAFC affirming more patent-holder victories and reversing more initial patent losses. Critics argue this could lead to easily issued patents lacking novelty or non-obviousness, potentially hindering innovation (Jaffe and Lerner, 2004).

The Trade-Related Aspects of Intellectual Property Rights (TRIPS) Agreement represents the next pivotal moment in the evolution of patent law. The agreement sets minimum international standards for World Trade Organization (WTO) member countries regarding intellectual property (IP) protection and enforcement, encompassing patents, copyrights, trademarks, and trade secrets. TRIPS aims for fair and non-discriminatory treatment of IP holders domestically and internationally. It mandates a baseline level of patent protection, including requirements for novelty, inventive step, industrial applicability, and minimum patent terms. To comply

[1] A summary of key legislative events impacting the US patenting market is provided in Appendix B.1. While this section highlights events that significantly influenced patent applications, Appendix B.1 offers a more comprehensive overview of the broader legislative landscape.

with TRIPS, the U.S. implemented modifications to its patent law on June 8, 1995. These changes primarily addressed the patent term, which refers to the maximum duration for which a patent grants its owner exclusive rights to an invention. Previously, patents were granted a term of 17 years from the date of issuance. The TRIPS-compliant amendment extended this protection to 20 years from the earliest filing date of the application. For applications submitted after June 8, the term was uniformly set at 20 years from filing. However, applications filed before this date offered assignees the option to choose the more advantageous term: either the traditional 17 years from issuance or the newly implemented 20 years from filing.

The final legislative development influencing the U.S. patenting market is the America Invents Act (AIA), signed into law on September 16, 2011, representing the most significant overhaul of the U.S. patent system since 1953 (Miyagiwa, 2015). The act's fundamental shift was from a "first-to-invent" to a "first-inventor-to-file" system for patent applications. This change aimed to streamline the patent process and bring US patent law more in line with international norms, where priority is given to the first person to file a patent application, regardless of the date of actual invention. This approach contrasts with the previous system, where the USPTO would often engage in complex and time-consuming procedures to determine the true first inventor. By eliminating this step, the AIA aimed to expedite the patenting process. The act also introduced the Post-Grant Review (PGR) and Inter Partes Review (IPR) procedures, which allow third parties to challenge the validity of a granted patent. PGR is available within the first 9 months of patent issuance and can address a broad range of issues, while IPR becomes available thereafter and is limited to prior art challenges. These procedures were implemented in September 2012, with the aim of improving the quality of patents.

The transition to a FITF system brought about significant strategic implications for patentees. Inventors now face increased pressure to file applications swiftly, prioritizing speed over the completeness of their supporting information. This urgency led to a surge in provisional applications (Merges, 2012), buying the inventor more time to refine their filing. Moreover, the AIA expanded the definition of prior art, potentially making it harder to prove the novelty and non-obviousness of inventions. In academic literature, this has sparked debates over the potential reduction in the quality of patents (Vandenburg, 2013), with scholars examining the trade-off between the increased accessibility to patent protection versus the potential for 'rushed' patents that have not been thoroughly developed or researched. It has also raised concerns over the disadvantages it might pose to smaller entities and individual inventors lacking the resources to navigate the hastened filing process (Abrams and Wagner, 2013; Case, 2013; Lerner et al., 2015).

Additionally, the AIA's post-grant procedures have been hot topics in both academic circles and the media. Some scholars have explored how PGR and IPR contribute to a more dynamic and contentious patent landscape, where patents can be continually reassessed and potentially invalidated or refined through post-grant challenges (Gatzemeyer, 2015). This continuous review process could help mitigate issues of overly broad or vague patents hurting the patent system. The media often frames these changes as a crackdown on so-called "bad patents" —entities that aggressively enforce patent rights beyond the patent's actual value or contribution to the market— thereby potentially fostering a more innovation-friendly environment (Kumar, 2017). However, there's an ongoing debate on the impact of such procedures on patent certainty and the increased legal costs they entail. The IPR process, in particular, has attracted considerable attention for its role in weakening patent rights by providing an efficient mechanism for competitors and other third parties (i.e. patent trolls) to challenge patents. Critics argue that these proceedings favor the challenger and add uncertainty to patent rights, which can deter investment in research and development (Tamimi, 2014).

The effects of the AIA on the patenting market are multifaceted. The race to the patent office incentivized by the first-to-file rule could expedite the disclosure of innovations but also skew the market in favor of larger, better-resourced companies that can manage frequent and fast patent filings. Small businesses and independent inventors without these resources could be disadvantaged, potentially stifling their contributions to innovation. The combination of first-inventor-to-file and post-grant proceedings may lead us to view the AIA as promoting a 'survival of the fittest' scenario, where only the most legally and financially robust firms can endure. This has generated extensive commentary on the need for strategic management of intellectual property portfolios, with corporations now having to navigate an increasingly complex patent landscape with a more aggressive and defensive orientation. The long-term effects of the AIA remain a subject of ongoing debate and academic scrutiny. While existing research is limited, it continues to assess whether the AIA promotes innovation or merely raises the cost and complexity of the patenting process.

2.2.2 Legislative Events and Patenting Activity

In this section, we discuss the relationship between the abovementioned legislative events in the US patent market and patenting activities of US corporations, both private and public, from 1980 to 2018. Figure 2.1a presents a visual representation of the number of patent applications submitted by US corporations, highlighting key legislative events with vertical lines.

The establishment of the Court of Appeals for the Federal Circuit (CAFC) on October 1, 1982, is associated with a noticeable spike in patent applications, suggesting a direct response to the enhanced consistency in patent law brought about by the CAFC (Hall and Ziedonis, 2001; Kortum and Lerner, 1999). The surge in applications, however, appears to begin in September 1982, potentially reflecting a transitional period during which firms, familiar with the previous system, may prefer to file applications before the CAFC's formal launch to avoid potential uncertainties. This period also coincides with a near tripling of US patent applications between 1980 and 2000 (Belenzon and Patacconi, 2013).

Another significant surge in patent applications occurs in 1995, coinciding with the enactment of the Trade-Related Aspects of Intellectual Property Rights (TRIPS) agreement, specifically the June 8th extension of patent terms. This surge can be attributed to the flexibility offered by the TRIPS agreement, which allowed patentees to choose a more favorable patent term, potentially motivating a pre-June 8th surge in applications to maximize potential patent protection. While the concurrent rise of the internet and advancements in telecommunications and software during the 1990s likely contributed to this surge, the TRIPS agreement may have further fueled it by potentially streamlining the patenting process. The upward trend in patent production appears to slow down around the beginning of the Great Recession in 2008, stabilizing throughout the remainder of the recessionary period until 2010.

The final surge observed in Figure 2.1a can be primarily attributed to the enactment of the America Invents Act (AIA), specifically the shift to the First-Inventor-to-File provision, which took effect on March 16, 2013. This change in priority rule appears to coincide with a significant rise in patent applications in March 2013, exhibiting a marked increase of 117% compared to February and 112% compared to the average for 2012. Following this surge, patent application volumes appear to return to their pre-AIA levels. Of the 22,579 applications filed in March 2013, 19,667 were submitted before the March 16th implementation date, suggesting that inventors might have preferred the older "first-to-invent" system, or sought to avoid perceived uncertainty associated with the new "first-inventor-to-file" provision, or both. This spike is also reflected in Figure 2.1b, which illustrates the annual percentage change in the number of patent applications, with significant increases corresponding to key events, particularly around the AIA implementation.

Figure 2.1c illustrates the trend in the total number of US firms filing at least one patent application from 1980 to 2018. In contrast to Figure 1.1a, the number of patent assignees appears to be increasing. However, due to data limitations on the total number of firms in the U.S. economy, it is unclear whether this increase reflects an expansion in firms engaged in innovative activities or simply indicates a rise in the overall number of firms. Figure 2.1d provides further insight, demonstrating a significant increase in the number of applicants associated with key legislative events, suggesting a correlation between these events and an expansion in firms engaged in innovation.

Figures 2.2a and 2.2b present the number of patent applications submitted by public and private firms, respectively. Figures 2.2c and 2.2d further delineate this data by firm size, distinguishing between small and large entities, focusing solely on public firms due to data limitations on private firms. Historically, patent application rates across these categories have exhibited a correlated growth pattern, even following the enactment of other legislative events. However, the implementation of the AIA appears to coincide with a divergence in this trend. Public firms appear to stabilize their application rates, while private firms demonstrate an increase in patent applications. Figures 2c and 2d reveal a similar pattern, with large public firms maintaining their application rates at pre-AIA levels, while small public firms appear to have reduced their application activity.

Legislative efforts other than the AIA have primarily focused on either streamlining and unifying patent law or changing patent terms. These changes have generally impacted all patent-holding entities in a similar manner. The AIA, however, distinguishes itself by introducing comprehensive changes to the patenting system that potentially have non-uniform consequences for different patent-generating entities.[2] This distinction raises the possibility that the AIA could induce significant structural shifts within the patent market. Evidence of such potential structural changes can be gleaned from the distinct patterns of patent application across various groups. Therefore, this study aims to investigate these asymmetries evident in the patenting activities of different groups of agents.

[2]Unreported analyses examining the impact of other legislations on patent applications did not reveal significant differences between small and large firms.

2.3 Sample Formation, Variables Definitions and Methodology

2.3.1 Data and Sample Formation

Our patent dataset includes all utility patents granted to entities identified as corporations or companies within the United States. To exclusively capture the innovative activities of U.S. firms, we exclude patents attributed to foreign entities, individual inventors, or government bodies. We utilize PatentView's Query Builder tool to filter the dataset, accordingly, resulting in a final count of 2,948,073 utility patents filed by U.S. corporations between 1980 and 2018. To further distinguish the patenting activity of publicly traded U.S. firms, we merged this sample with the patent dataset provided by Kogan et al. (2017). This dataset links patent information with details on publicly traded companies, enabling us to specifically analyze the patenting behavior of these firms and, separately, the rest, i.e. private firms. While this approach enables a comparative analysis of patenting activities between publicly traded and privately held firms, the lack of data on private firms limits the scope of our analysis. As a result, our findings regarding private firms are primarily descriptive.

For firm-level analysis, we use yearly panel data of firms that filed at least one utility patent between 1980 and 2018 (Kogan et al., 2017). We merge this dataset with the CRSP-Compustat database, resulting in 47,353 firm-year level observations spanning from 1980 to 2018.

2.3.2 Patenting Activity Measures

At the aggregate level, we analyze yearly patent applications by U.S corporations and calculate the percentage change in applications to capture the growth in patenting activity. To assess firm-level innovation, we track the number of patent applications filed by each (public) firm annually (*Patent Applications*). To investigate the speed at which firms obtain patents, we calculate the median number of days between application and grant dates for each firm-year observation. We further explore the quality of firm innovation by calculating several metrics: median quality, high-quality patents, and breakthrough patents. *Median Quality* is determined for each firm-year by calculating the median KPSS values of its patents. *High-quality* Patents represent the number of patents filed by a firm that exceed the median KPSS of all patents filed that year. Similarly, *Breakthrough Patents* capture the number of patents filed by a firm that exceed the 90$^{\text{th}}$ percentile of all patent KPSS values in a given year (Kerr, 2010).

2.3.3 Empirical Methodology

To assess the changes in overall innovative activity of U.S. companies, we estimate the following regression equation for the years t, ranging from 1980 to 2018.

$$
\begin{aligned}
\text{Patenting Activity}_t = {} & \beta_1 \text{ Post-AIA}_t + \text{Patenting Activity}_{t-1} \\
& + \Delta\text{GDP}_{t-1} + \Delta\text{Domestic Credit}_{t-1} \\
& + \text{Election Year}_t + \epsilon
\end{aligned}
\tag{2.1}
$$

The dependent variable, *Patenting Activity*, is captured by two measures: the yearly patent applications made by U.S companies (*Patent Applications*) and the annual growth rate of patent applications (ΔPatent Applications). The variable of interest, *Post-AIA(Enactment) (Post AIA(Implementation))*, is a dummy variable that equals 1 for years following the enactment (implementation) of the AIA and 0 for years prior to the enactment (implementation). The model incorporates several control variables, namely changes in Gross Domestic Product (*%Change in GDP*), changes in Domestic Credit (*%Change in Domestic Credit*), and *Election Year* Dummy, which are recognized as influential factors on aggregate-level innovation within an economy (Bhattacharya et al., 2017; Furman et al., 2002).

To assess the changes in innovative activity of U.S. companies in the firm level, we estimate Equation 2.2 for public firm i and time t. The dependent variable in this equation is patenting activity, which serves as a proxy for a firm's innovative output. As detailed in the previous section, we employ five alternative measures to capture patenting activity: *Patent Applications*, *Days to Grant*, *Median Quality*, *High-Quality Patents* and *Breakthrough Patents*. Our model incorporates a set of control variables ($Z_{i,\,k,\,t-1}$) known to affect firm-level innovation (Chemmanur and Tian, 2018; Sevilir and Tian, 2023). These variables encompass firm size, R&D intensity, return on assets, asset tangibility, market valuation, industry concentration, and market leverage. Detailed definitions of these variables are provided in

Appendix A.1 of the preceding chapter. Further, we include industry-fixed effects ($\alpha_{IND,i}$) to account for systematic differences across industries.

$$\text{Patenting Activity}_{i,t} = \beta_1 \text{ Post-AIA}_t + \beta_k \sum Z_{i,\,k,\,t-1} + \alpha_{IND,i} + \epsilon_{i,t} \tag{2.2}$$

To further investigate the potential heterogeneous effects of the legislation on firms of varying sizes, we employ a difference-in-differences model (Equation 2.3). The key variable of interest is the interaction term between a post-implementation dummy variable (*Post AIA*), which takes a value of 1 for years subsequent to the implementation of the priority rule, and a *Small Firm* dummy variable, which is assigned a value of 1 to firms with total assets below the median for that particular year. The model incorporates the same control variables and industry-fixed effects as the previous analysis.

$$\begin{aligned}\text{Patenting Activity}_{i,t} = \beta_1 \text{ Post-AIA}_t \times \text{Small Firm} \\ + \beta_k \sum Z_{i,\,k,\,t-1} + \alpha_{IND,i} + \epsilon_{i,t}\end{aligned} \tag{2.3}$$

Given the inherent characteristics of our dependent variables, i.e., their disproportionate concentration at zero and high skewness, we adopt a negative binomial model for estimating Equation 2.2 and 2.3 (Wooldridge, 2010). This approach is particularly suited for dealing with overdispersed count data, ensuring higher efficiency and robustness in our analysis (Chen et al., 2023; Cohn et al., 2022). To ensure the robustness of statistical inferences, all models incorporate robust standard errors adjusted for heteroscedasticity.

2.3.4 Summary Statistics

Table 2.1 provides an overview of the internal innovation market in the United States before and after the AIA. To ensure valid comparisons and minimize the influence of long-term firm evolution, we constructed pre-and post- measures by analyzing a 5-year window both before and after the implementation of the AIA. Panel A focuses on patenting activity across all U.S. corporations, including both public and private firms. It presents yearly data on patent applications from 2000 to 2018 and the distribution of patent applications between private and public firms within this timeframe. Our initial analysis reveals a slight rise in patent applications across all firms, including both public and private entities. When examining public firms in isolation, the upward trend seems to persist. However, the percentage change in applications filed by both public and private corporations appears to decline after 2011, with a more significant decrease observed for public firms. This might suggest a potential dampening effect of the AIA on the patenting activity.

Our analysis also points to a possible change in the market composition since the year 2000: the percentage of public firms among all innovative U.S. corporations seems to be decreasing. However, it's crucial to acknowledge a limitation here: without data on the overall composition of U.S. corporations, we cannot definitively conclude whether this decrease reflects a general trend or is specific to innovation market. The lack of data on the broader market composition restricts our ability to draw conclusive inferences from this observation.

Panel B further investigates firm-level innovation activity and applicant characteristics, comparing pre- and post-AIA periods. While definitive conclusions require further analysis, our descriptive statistics offer initial insights. Patent applications exhibit a slight increase post-AIA, potentially reflecting an initial surge in activity. The AIA's goal of faster processing times appears to be met, with a significant decrease in *Days to Grant*. Additionally, there is an upward trend in quality measures during the post-AIA period. However, it's crucial to acknowledge the limitations of descriptive statistics in establishing causality.

Firm size data aligns with existing literature, indicating a potential shift towards larger applicants in the post-AIA period. This is evidenced by higher total assets among patent applicants following the legislation's implementation. Interestingly, R&D intensity doesn't show a difference pre- versus post-AIA. Furthermore, a rise in the market-to-book ratio suggests that firms with potentially higher valuations are more likely to pursue patents post-AIA.

2.4 Empirical Evidence

2.4.1 Aggregate Trends: Examining the AIA's Impact on Patenting Ac-

tivity

We examine the impact of the AIA and its associated priority rule change on overall patenting activity. Table 2.2 presents the regression output for the empirical model shown in Equation 2.1.

Our findings align with the existing literature, indicating a decrease in patenting activity after the AIA (Abrams and Wagner, 2013; Lo and Sutthiphisal, 2009). Specifically, the coefficient of -0.294 in Column (1) indicates a 34.17% decrease in patent applications after the Act's enactment, while the coefficient of -0.432 in Column (2) suggests a 54.03% decrease following its implementation. Columns (3) and (4) further reveal a reduction in the growth rate of patent applications after both the enactment and implementation of the AIA. This observation may suggest that the AIA has initiated a period of stagnation in patent application activity, potentially posing a risk to the future of the innovation market.

Furthermore, these findings provide empirical support for the significant negative coefficients on "Post" variables observed in the preceding chapter. However, the current analysis expands upon the previous chapter by including private firms within the sample. This expanded sample allows for a broader examination of the impact on internal innovation activities, particularly the observed decline in such activities.

2.4.2 The Firm-Level Perspective: AIA's Impact on Patenting Activity

We next investigate the impact of the AIA on patenting activity at the firm level. Tables 2.3 and 2.4 present regression results based on Equation 2.2, analyzing both the quantity and speed of patenting activity, as well as the quality of patents obtained.

Table 2.3 focuses on the impact of the AIA on patent application filing and the time taken to secure a patent. The first two columns demonstrate a significant reduction in patent applications filed by publicly traded firms, with a 19.00% decrease following the AIA's enactment and an 17.23% decrease following the implementation of priority rule change. This finding corroborates the decline in patenting activity observed at the aggregate level. Columns (3) and (4) demonstrate a reduction in the time required to obtain a patent, with a 16.64% decrease following enactment and a 20.20% decrease following implementation of the AIA. These findings suggest that the Act has successfully expedited the patenting process. This expedited processing, however, appears to have come at the cost of reduced patent applications.

The competitive nature of the new system, with its increased expected costs, likely contributed to this unintended consequence.

Table 2.4 examines the impact of the AIA on patent quality. The dependent variables, representing patent quality, are categorized into three groups: *Median Quality* (Columns (1) and (2), *High-Quality Patents* (Columns (3) and (4)), and *Breakthrough Patents* (Columns (5) and (6)). The findings indicate a general decline in patent quality following both the enactment and implementation of the AIA. Specifically, the first column reveals a 10.52% decrease in the median quality of patents issued to firms after the AIA's enactment. This decrease in average quality is further supported by the last four columns, which show a decline in the number of high-quality and breakthrough patents produced by public firms. Column (3) demonstrates a 20.92% reduction in the number of higher-quality patents, while Column (5) shows a significantly larger drop of 66.20% in the number of breakthrough patents following the AIA's enactment. These results also hold after considering the impact of the AIA's implementation.

While the USPTO successfully achieved its objective of faster patent grants through the AIA, this expedited process has been accompanied by a simultaneous decline in patent applications and patent quality. This highlights a potential trade-off between patent processing speed and overall patenting activity, necessitating further investigation into the long-term implications of these findings for innovation and economic competitiveness.

2.4.3 Unpacking the Size Gap: The AIA's Influence on Patenting Activity in Small and Large Firms

This section investigates whether the AIA differentially affect firms of varying sizes. Tables 2.5 and 2.5 present the regression results for the DID model specified in Equation 2.3.

Table 2.5 examines the relationship between firm size and two dependent variables: the number of patent applications filed by a firm and the median time elapsed between application and grant dates of patents obtained by a firm within a given year. The findings reveal significant asymmetries across firm size categories. Specifically, Column (1) indicates that firms with total assets below the median level exhibit a 16.42% reduction in patent applications compared to their larger counterparts following the implementation of the AIA. The negative and statistically significant coefficient associated with the *Small Firm (Median)* variable suggests that smaller firms historically filed fewer patent applications prior to the AIA. However, the interaction term highlights a further widening of this gap post-AIA, indicating a substantial decrease in patent applications among smaller firms following the legislation's enactment. Column (2) further refines the size categories to capture potential non-linear effects within the firm size spectrum. This analysis defines small firms as those with total assets below the 10^{th} percentile and large firms as those with total assets above the 90^{th} percentile. The objective is to examine the patenting activity of these extreme size categories. The results suggest that the largest ones produce significantly higher patents, 23% higher, while we do not find a significant change in the lower 10 percentile following the AIA.

A noteworthy finding emerges from the analysis: following the implementation of the AIA, patent applications filed by smaller firms experience a faster grant process. Specifically, the coefficient for the interaction term *Small Firm (Median)* × *Post-AIA* in Column (3) indicates a 17.47% reduction in the time required for smaller firms to obtain patents compared to their larger counterparts. Similarly, Column (4) reveals that firms with total assets below the 10^{th} percentile experience a significantly shorter processing time (10.99%), while firms exceeding the 90^{th} percentile exhibit a notably longer duration (18.77%). This observation may be attributed to several potential factors. One explanation could be that larger firms tend to pursue patents for more complex inventions, necessitating extensive research to establish novelty. Alternatively, smaller firms might prioritize the preparation of well-drafted applications with clear and concise descriptions of their inventions, leading to a more efficient processing.

The positive and statistically significant coefficient associated with the *Small Firm (Median)* variable offers some insight into this phenomenon. It suggests that prior to the AIA, patent applications from smaller firms took longer to be granted. However, this relationship reverses following the implementation of the AIA. If the complexity of larger firms' inventions has not increased significantly since the AIA, it seems likely that the improved efficiency of smaller firms in preparing applications might be the primary driver of this observation. This could be due to a selection effect, where smaller firms that remain in the market post-AIA are those that have successfully adapted to the new environment and are able to produce high-quality patent applications.

Table 2.6 investigates the quality of patents across firms of different sizes. While there does not appear to be a significant change in the average median quality of patents for *Small Firms (Median)*, it is evident that the largest firms are producing patents of lower quality, indicated by the significant negative coefficient on *Large Firm (p90)* $\times$ *Post-AIA* in Column (2). Our findings consistently indicate a decline in the number of high-quality and breakthrough patents produced by large firms. The coefficients on the interaction terms across the last four columns are negative and statistically significant at the 1% level for both firms larger than the median and those at the 90$^{\text{th}}$ percentile.

Interestingly, the results for smaller firms exhibit a more nuanced picture. Our findings for small firms show a reversal from *Small Firm (Median)* to *Small Firm (p10)*. Specifically, the coefficient on *Small Firm (Median)* $\times$ *Post-AIA* is positive and significant in Columns (3) and (5), suggesting a potential increase in high-quality patents for median-sized small firms after the AIA. Conversely, the coefficient on *Small Firm (p10)* $\times$ *Post-AIA* is negative in Columns (4) and (6), indicating a decrease in the number of quality patents for the very smallest firms that are below the 10$^{\text{th}}$ percentile. To further investigate this reversal, we break down small sizes, and the results of this analysis are presented in Table 2.7. The analysis reveals a critical shift after the 25$^{\text{th}}$ percentile. Smaller-to-medium firms, specifically those with total assets larger than the 25$^{\text{th}}$ percentile but smaller than the median, demonstrate a relative increase in high-quality and breakthrough patents compared to other size categories.[3] This observation could be attributed to these firms facing a competitive disadvantage in producing a large volume of patents. As a result, they prioritize producing higher-quality patents to secure their position in the market.

Overall, our results in this section suggest a differential and non-linear impact of the AIA across firm sizes. While small-to-medium sized firms, particularly those between the 25$^{\text{th}}$ and 50$^{\text{th}}$ percentile, exhibit an increase in the quality of their patents despite a potential decrease in overall patenting activity, larger firms demonstrate an increased patenting activity coupled with a decline in patent quality. The smallest firms, on the other hand, seem to have been pushed out of the patenting market altogether. These findings highlight the complex interplay between firm size, the AIA, and patenting activity.

Furthermore, our findings corroborate existing literature that has documented an exit of small inventors from the patenting market following the enactment of the America Invents Act (AIA) (Abrams and Wagner, 2013; Lerner et al., 2015). However, a gap exists in the literature regarding the impact of the AIA on patent appli-

[3] To further examine the impact of the AIA on patent quality for medium-sized firms, we define the medium size group as those with total assets below the median but above the 25$^{\text{th}}$ percentile. Re-running the same tests for this specific firm size category yields significant positive coefficients for the post-AIA period, statistically significant at the 1% level. These unreported findings support the observation that medium-sized firms, particularly those exceeding the 25$^{\text{th}}$ percentile in total assets, experience a notable increase in the number of quality patents after the implementation of the AIA.

cations from small public corporations. Prior studies have typically defined "small entities" as individual inventors or small firms eligible for discounted patent application fees, thus excluding public firms from their analysis. This distinction is crucial, as our previous chapters have focused on small public firms, and we find that only 3% of public firms fall into the category typically defined as "small" in the literature. This suggests that these firms may not be as small as initially perceived, prompting a need for further exploration. To bridge this gap in the existing body of knowledge, this section provides separate findings on patent applications from small public corporations, offering a more comprehensive analysis of the topic previously discussed in the preceding chapters.

2.5 Robustness Analysis

2.5.1 The AIA's Influence on Internal Innovation: A Robustness Check Excluding Other Major Legislations

To assess the isolated impact of the AIA, we conducted a robustness analysis by excluding data prior to 2000, effectively removing the potential influence of other major legislations during our sample period. This analysis, presented in Table 2.8, demonstrates that our findings regarding the AIA's effect on internal innovation remain consistent.

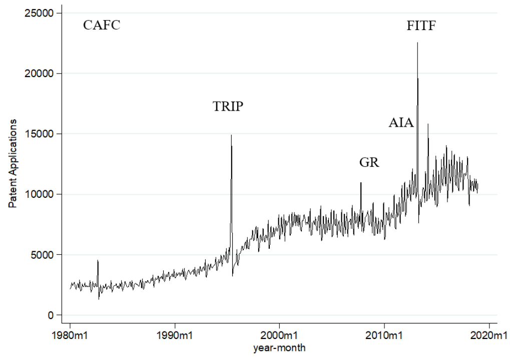
2.5.2 Falsification Tests

To mitigate the risk of attributing observed results to factors other than the Act itself (Angrist and Krueger, 1999), we conduct falsification tests. These tests involve introducing a random event date at least four years prior to the Act's implementation, ensuring no overlap with the pre-AIA period used in our baseline analyses. We replicate our analyses using this placebo event date (September 26, 2004). The results, shown in Table 2.9, demonstrate the robustness of our findings regarding the AIA's impact on internal innovation.

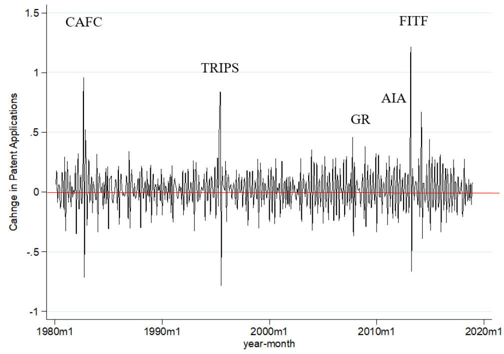
2.6 Conclusion

The America Invents Act (AIA) has had a multifaceted impact on the U.S. patenting landscape. While the USPTO achieved its goal of faster patent grants, this came at the cost of a decline in overall patenting activity and a concerning decrease in patent quality, particularly among larger firms. Our findings reveal a significant disparity in the effects on firms of varying sizes. Smaller-to-medium-sized firms appear to have adapted by prioritizing higher-quality patents over quantity. Conversely, the AIA seems to have disadvantaged the very smallest firms, potentially pushing them out of the patenting market altogether. Larger firms, on the other hand, exhibit a concerning trend of increased patenting activity coupled with a decline in patent quality. These results highlight a potential structural change in the innovation ecosystem. Further research is necessary to understand the long-term implications of the AIA on U.S. competitiveness and to explore potential policy adjustments that could mitigate unintended consequences.

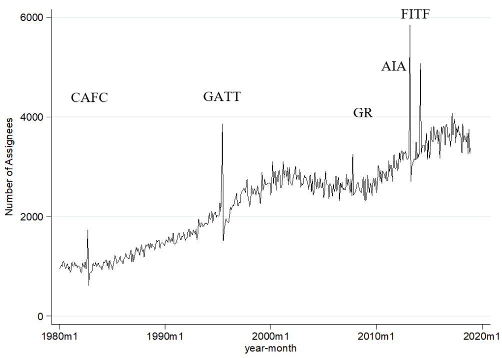
2.7 Tables and Figures



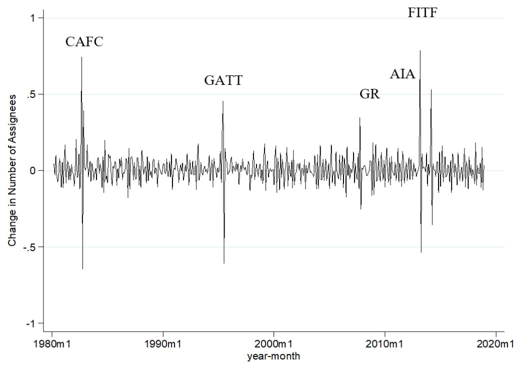
(a) This figure presents the monthly volume of utility patent applications submitted by U.S. corporations from 1980 to 2018. The vertical lines highlight key legislative and economic events that occurred during this period. These events include: the establishment of Court of Appeals for the Federal Circuit (October 1982), the enactment of the General Agreement on Tariffs and Trade (June 1995), the Great Recession (September 2008), the enactment of the America Invents Act (September 2011), the implementation of the priority rule change from "first-to-invent" (FTI) to "first-to-file" (FITF) (March 2013).



(b) This figure presents the monthly change in utility patent applications filed by U.S. corporations over the period 1980-2018.

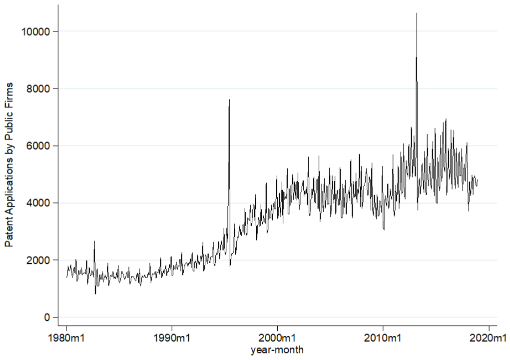


(c) This figure presents the monthly number of U.S. firms filing at least one utility patent application from 1980 to 2018. As in Figure 2.1a, vertical lines highlight key legislative and economic events that may have influenced patenting activity.

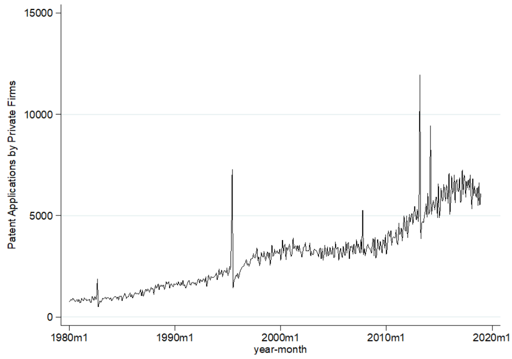


(d) This figure presents the monthly change in U.S. firms filing at least one utility patent application from 1980 to 2018.

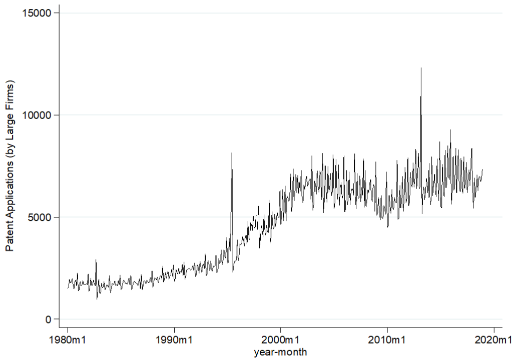
Figure 2.1 Utility Patent Applications by U.S. Firms (1990-2018)



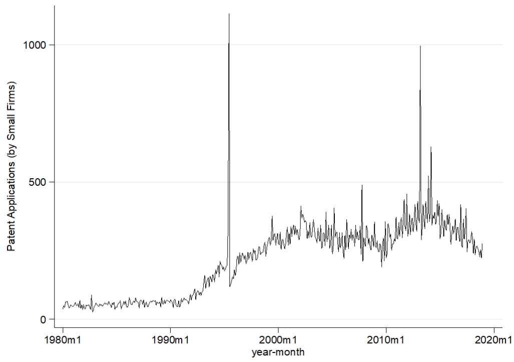
(a) This figure presents the monthly number of utility patent applications submitted by U.S. *public* corporations from 1980 to 2018. As in Figure 2.1a, vertical lines highlight key legislative and economic events that may have influenced patenting activity.



(b) This figure presents the monthly volume of utility patent applications submitted by U.S. *private* corporations from 1980 to 2018.



(c) This figure presents the monthly number of utility patent applications submitted by large (higher than the median total asstes) U.S. *public* corporations from 1980 to 2018.



(d) This figure presents the monthly number of utility patent applications submitted by small (lower than the median total asstes) U.S. *public* corporations from 1980 to 2018.

Figure 2.2 Utility Patent Applications by U.S. Firm Type and Size (1990-2018)

Table 2.1 Summary Statistics

This table provides a descriptive overview of the U.S. internal innovation market. Panel A analyzes the composition of patent applications, distinguishing between those filed by publicly and privately held companies from 2000 to 2018. Panel B focuses on the patenting activities of innovative public firms. It compares firm characteristics of innovative public firms 5 years before (2008-2012) and 5 years after (2014- 2018) the implementation of the AIA. Detailed information on patent-related variables and firm characteristics is provided in Section 2.3.2 and Appendix A.1, respectively.

Panel A. Composition of U.S. Patent Applications: Public vs. Private Firms (2000-2018)

Year	*All Patent Applications*	*% Change in All Applications*	*Patent Applications by Public Firms*	*% Change in Public Firm Applications*	*% Public*
2000	88.887	0.082	76.749	0.120	0.863
2001	92.407	0.040	84.161	0.097	0.911
2002	92.789	0.004	86.360	0.026	0.931
2003	90.432	-0.025	85.843	-0.006	0.949
2004	88.049	-0.026	83.322	-0.029	0.946
2005	89.409	0.015	82.996	-0.004	0.928
2006	90.742	0.015	80.985	-0.024	0.892
2007	95.754	0.055	81.898	0.011	0.855
2008	95.798	0.000	81.355	-0.007	0.849
2009	89.377	-0.067	71.766	-0.118	0.803
2010	95.865	0.073	73.298	0.021	0.765
2011	105.446	0.100	78.595	0.072	0.745
2012	121.862	0.156	88.330	0.124	0.725
2013	129.643	0.064	88.171	-0.002	0.680
2014	131.131	0.011	86.048	-0.024	0.656
2015	134.800	0.028	88.260	0.026	0.655
2016	138.483	0.027	88.098	-0.002	0.636
2017	140.014	0.011	88.320	0.003	0.631
2018	127.541	-0.089	82.713	-0.063	0.649

Table 2.1 – Continued from previous page

Panel B. Patenting Activity and Innovative Firm Characteristics: Pre-AIA vs. Post-AIA

	Pre-AIA			Post-AIA		
	Mean	**Median**	**N**	**Mean**	**Median**	**N**
Patenting Activity						
Log (Patent Applications)	2,218	1,792	6750	2,496	2,496	5159
Patent Applications	58,273	5	6750	84,016	7	5159
Days to Grant	1169,05	1106	6750	878,514	844	5159
Median Quality	9,215	2,792	6750	15,112	4,325	5159
High-Quality Patents	29,137	1	6750	42,011	2	5159
Breakthrough Patents	5,829	0	6750	8,406	0	5159
Firm Characteristics						
Firm Size	6,887	6,762	5.619	7,203	7,134	4.846
RD Intensity	0,134	0,070	4,961	0,139	0,073	4358
ROA	-0,063	0,037	5.619	-0,086	0,027	4.846
Asset Tangibility	0,183	0,129	5.619	0,169	0,109	4.846
Log(market-to-book)	0,855	0,788	5.406	1,211	1,124	4.640
Leverage	0,245	0,195	5.582	0,294	0,288	4.818

Table 2.2 The Impact of AIA on Aggregate Patenting Activity

This table presents the regression results indicating the impact of AIA on aggregate patenting activity by estimating Equation 2.1. The dependent variables are *Patent Applications*, the number of patents filed by U.S. corporations in a year, and Δ*(Patent Applications)*, the percent changes in yearly patent applications. The construction of the dependent variables is explained in Section 2.3.2. *Post-AIA (Enactment)* is a binary variable that takes the value of one if the year falls after the enactment of the AIA in 2011 and zero otherwise. *Post-AIA (Implementation)* is a binary variable that takes the value of one if the year falls after the implementation of the priority rule change in 2013 and zero otherwise. Data for control variables, including *Change in GDP* and *Change in Domestic Credit*, come from the World Bank dataset. We employ robust standard errors adjusted for heteroscedasticity. t-values are enclosed in parentheses below the reported coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Variables	*Patent Applications* (1)	*Patent Applications* (2)	Δ*(Patent Applications)* (3)	Δ*(Patent Applications)* (4)
Post-AIA (Enactment)	-0.294***		-0.0137	
	(-3.543)		(-0.502)	
Post-AIA (Implementation)		-0.432***		-0.0485*
		(-8.854)		(-1.910)
L.Patent Applications	0.001***	0.001***		
	(21.45)	(28.90)		
%Change in GDP	0.517	1.019	0.670	0.659
	(0.422)	(1.007)	(1.276)	(1.209)
%Change in Domestic Credit	0.445	0.183	0.0262	-0.0814
	(0.834)	(0.384)	(0.0889)	(-0.295)
Election Year Dummy	0.0415	-0.0183	-0.00646	-0.0128
	(0.715)	(-0.513)	(-0.213)	(-0.446)
L.Δ*(Patent Applications)*			0.129	0.105
			(0.530)	(0.421)
Constant	9.907***	9.874***	0.0228	0.0327*
	(166.6)	(194.2)	(1.389)	(1.979)
Observations	37	37	36	36
R^2	0.1243	0.1374	0.061	0.120

Robust z-statistics in parentheses.

***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$

Table 2.3 The Impact of AIA on Firm-Level Patenting Activity

This table presents the regression results indicating the impact of AIA on firm-level patenting activity. Equation 2.2 is estimated using a negative binomial model. The dependent variables are *Patent Applications*, the yearly number of patents filed by public firms, and *Days to Grant*, the median time (in days) between application and grant dates for each firm-year. The construction of the dependent variables is explained in Section 2.3.2. *Post-AIA (Enactment)* is a binary variable that takes the value of one if the year falls after the enactment of the AIA in 2011 and zero otherwise. *Post-AIA (Implementation)* is a binary variable that takes the value of one if the year falls after the implementation of the priority rule change in 2013 and zero otherwise. Refer to Appendix A.1 for detailed definitions of the control variables. All continuous variables are winsorized at their 1st and 99th percentiles. All specifications include industry-fixed effects. We employ robust standard errors adjusted for heteroscedasticity. t-values are enclosed in parentheses below the reported coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Variables	*Patent Applications* (1)	*Patent Applications* (2)	*Days to Grant* (3)	*Days to Grant* (4)
Post-AIA (enactment)	-0.174***		-0.154***	
	(-7.846)		(-23.07)	
Post-AIA (implementation)		-0.159***		-0.184***
		(-5.954)		(-23.99)
Size	0.688***	0.686***	0.042***	0.041***
	(145.3)	(147.3)	(27.36)	(27.48)
R&D Intensity	2.334***	2.295***	-0.022	-0.0331
	(20.64)	(20.44)	(-0.640)	(-0.962)
ROA	0.0531	0.0426	-0.148***	-0.153***
	(1.070)	(0.863)	(-8.686)	(-8.992)
Asset Tangibility	0.824***	0.891***	-0.579***	-0.569***
	(12.57)	(13.73)	(-26.63)	(-26.45)
Log (Market-to-Book)	0.179***	0.181***	0.052***	0.055***
	(17.56)	(17.81)	(14.86)	(15.58)
HHI	0.908***	0.893***	-0.182***	-0.175***
	(4.726)	(4.626)	(-2.784)	(-2.697)
HHI square	-0.856***	-0.857***	0.244***	0.241***
	(-4.438)	(-4.424)	(3.514)	(3.474)
Market Leverage	-0.413***	-0.409***	-0.149***	-0.147***
	(-10.68)	(-10.61)	(-12.27)	(-12.24)
Constant	-1.848***	-1.850***	6.696***	6.690***
	(-16.95)	(-16.94)	(139.9)	(140.1)
Observations	29,838	29,821	29,838	29,821
Pseudo R^2	0.1685	0.1688	0.0149	0.0151

Robust z-statistics in parentheses.

***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$

Table 2.4 Quality of Internal Innovation

This table presents the regression results indicating the impact of AIA on patent quality by estimating Equation 2.2 using a negative binomial model. The dependent variables are *Median Quality*, the median KPSS value of patents a firm applied in a given year, *High-Quality Patents*, the number of patents filed by a firm that exceed the median KPSS value for that year, and *Breakthrough Patents*, the number of patents filed by a firm that exceed the 90th percentile KPSS value within the same year. The construction of the dependent variables is explained in Section 2.3.2. *Post-AIA (Enactment)* is a binary variable that takes the value of one if the year falls after the enactment of the AIA in 2011 and zero otherwise. *Post-AIA (Implementation)* is a binary variable that takes the value of one if the year falls after the implementation of the priority rule change in 2013 and zero otherwise. Refer to Appendix A.1 for detailed definitions of the control variables. All continuous variables are winsorized at their 1st and 99th percentiles. All specifications include industry-fixed effects. We employ robust standard errors adjusted for heteroscedasticity. t-values are enclosed in parentheses below the reported coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Median Quality	*Median Quality*	*High-Quality Patents*	*High-Quality Patents*	*Breakthrough Patents*	*Breakthrough Patents*
	(1)	(2)	(3)	(4)	(5)	(6)
Post AIA	-0.10***		-0.19***		-0.508***	
(enactment)	(-3.299)		(-15.27)		(-16.82)	
Post AIA		-0.055		-0.186***		-0.550***
(implementation)		(-1.468)		(-12.73)		(-16.40)
Size	0.444***	0.439***	0.430***	0.420***	0.750***	0.744***
	(53.33)	(52.92)	(129.8)	(130.4)	(84.34)	(84.46)
R&D Intensity	0.092	0.096	1.473***	1.649***	2.060***	1.907***
	(0.296)	(0.314)	(16.84)	(19.86)	(8.441)	(7.831)
ROA	0.440***	0.438***	0.677***	0.928***	1.121***	1.044***
	(3.600)	(3.654)	(12.40)	(15.44)	(6.861)	(6.538)
Asset Tangibility	0.065	0.135**	0.229***	-0.0579*	0.592***	0.746***
	(0.965)	(2.038)	(5.058)	(-1.670)	(5.364)	(6.910)
Log(Market-to-Book)	0.611***	0.610***	0.244***	0.263***	0.542***	0.563***
	(52.70)	(52.83)	(33.05)	(33.94)	(27.80)	(28.85)
HHI	0.524**	0.530**	0.107	-0.46***	2.147***	2.169***
	(2.505)	(2.541)	(0.843)	(-5.434)	(6.339)	(6.326)
HHI square	-0.986***	-0.980***	-0.249**	0.384***	-2.286***	-2.300***
	(-4.743)	(-4.741)	(-2.034)	(4.232)	(-6.978)	(-6.976)
Market Leverage	-0.486***	-0.493***	-0.256***	-0.353***	-0.847***	-0.832***
	(-8.834)	(-8.837)	(-9.556)	(-13.11)	(-11.73)	(-11.52)
Constant	-1.793***	-1.783***	-2.860***	-2.872***	-7.123***	-7.149***
	(-12.76)	(-12.76)	(-42.04)	(-92.15)	(-37.31)	(-36.80)
Observations	29,838	29,821	29,838	29,821	29,838	29,821
Pseudo R^2	0.1714	0.1709	0.2080	0.2525	0.3124	0.3117

Robust z-statistics in parentheses.

***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$

Table 2.5 Post AIA Patenting Activity by Firm Size

This table presents the regression results indicating the impact of AIA on patent activity by size. It employs a negative binomial model to estimate Equation 2.3. The dependent variables are *Patent Applications*, the yearly number of patents filed by public firms, and *Days to Grant*, the median time (in days) between application and grant dates for each firm-year. *Post-AIA (Implementation)* is a binary variable that takes the value of one if the year falls after the implementation of the priority rule change in 2013 and zero otherwise. *Small Firm (Median)* is a binary indicator assigned a value of 1 if a firm's total assets are below the median total assets for that year, and 0 otherwise. *Small Firm (p10)* is a binary indicator that takes the value of 1 if the firm's total assets fall below the 10^{th} percentile in that year, and 0 otherwise. *Large Firm (p90)* is a binary indicator set to 1 if a firm's total assets exceed the 90^{th} percentile for that year, and 0 otherwise. Refer to Appendix A.1 for detailed definitions of the control variables. All continuous variables are winsorized at their 1^{st} and 99^{th} percentiles. All specifications include industry-fixed effects. We employ robust standard errors adjusted for heteroscedasticity. t-values are enclosed in parentheses below the reported coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Variables	*Patent Applications* (1)	*Patent Applications* (2)	*Days to Grant* (3)	*Days to Grant* (4)
Post AIA (implementation)	0.511***	0.392***	-0.0803***	-0.171***
	(11.03)	(11.71)	(-8.933)	(-19.85)
Small Firm (Median)	-2.010***		0.0164**	
	(-71.33)		(2.286)	
Small Firms (p10)		-1.050***		-0.0441**
		(-18.61)		(-2.396)
Large Firm (p90)		2.482***		-0.0351***
		(90.91)		(-4.915)
Post AIA (implementation)	-0.152**		-0.161***	
× *Small Firm (Median)*	(-2.536)		(-10.49)	
Post AIA (implementation)		0.160		-0.0943**
× *Small Firm (p10)*		(1.211)		(-2.496)
Post AIA (implementation)		0.208***		0.172***
× *Large Firm (p90)*		(3.001)		(10.04)
Size	0.879***	0.729***	-0.162***	-0.157***
	(7.852)	(4.943)	(-4.738)	(-4.593)
R&D Intensity	0.823***	0.861***	-0.0697***	-0.0800***
	(12.95)	(9.570)	(-4.070)	(-4.625)
ROA	0.701***	0.0744	-0.550***	-0.549***
	(7.920)	(0.895)	(-25.54)	(-25.51)
Asset Tangibility	0.176***	0.222***	0.0544***	0.0565***
	(12.21)	(16.68)	(15.34)	(15.94)
Log (Market-to-Book)	0.812***	0.402*	-0.226***	-0.216***
	(2.752)	(1.666)	(-3.449)	(-3.303)
HHI	0.0946	-0.0981	0.318***	0.313***

Table 2.5 – Continued from previous page

Variables	*Patent Applications* (1)	*Patent Applications* (2)	*Days to Grant* (3)	*Days to Grant* (4)
	(0.326)	(-0.404)	(4.579)	(4.509)
HHI square	0.191***	0.375***	-0.0818***	-0.0775***
	(4.048)	(8.724)	(-6.921)	(-6.691)
Market Leverage	3.499***	2.066***	6.925***	6.928***
	(17.98)	(15.52)	(159.0)	(158.7)
Observations	29,821	29,821	29,821	29,821
Pseudo R^2	0.1002	0.1262	0.0134	0.0135

Robust z-statistics in parentheses.

***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$

Table 2.6 Quality of Internal Innovation by Firm Size

This table presents the regression results indicating the impact of AIA on patent activity by size. It employs a negative binomial model to estimate Equation 2.3. The dependent variables are *Median Quality*, the median KPSS value of patents a firm applied in a given year, *High-Quality Patents*, the number of patents filed by a firm that exceed the median KPSS value for that year, and *Breakthrough Patents*, the number of patents filed by a firm that exceed the 90^{th} percentile KPSS value within the same year. *Post-AIA (Implementation)* is a binary variable that takes the value of one if the year falls after the implementation of the priority rule change in 2013 and zero otherwise. *Small Firm (Median)* is a binary indicator assigned a value of 1 if a firm's total assets are below the median total assets for that year, and 0 otherwise. *Small Firm (p10)* is a binary indicator that takes the value of 1 if the firm's total assets fall below the 10^{th} percentile in that year, and 0 otherwise. *Large Firm (p90)* is a binary indicator set to 1 if a firm's total assets exceed the 90^{th} percentile for that year, and 0 otherwise. Refer to Appendix A.1 for detailed definitions of the control variables. All continuous variables are winsorized at their 1^{st} and 99^{th} percentiles. All specifications include industry-fixed effects. We employ robust standard errors adjusted for heteroscedasticity. t-values are enclosed in parentheses below the reported coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Median Quality	*Median Quality*	*High-Quality Patents*	*High-Quality Patents*	*Breakthrough Patents*	*Breakthrough Patents*
	(1)	(2)	(3)	(4)	(5)	(6)
Post AIA (Implementation)	0.409***	0.404***	0.181***	0.360***	0.0764**	0.341***
	(14.82)	(15.36)	(11.42)	(19.11)	(2.006)	(6.307)
Small Firm (Median)	-1.52***		-1.885***		-3.512***	
	(-53.62)		(-66.68)		(-30.71)	
Post AIA (Implementation) × *Small Firm (Median)*	0.0523		0.446***		0.961***	
	(0.861)		(9.135)		(5.234)	
Small Firms (p10)		-1.393***		-2.462***		-3.123***
		(-18.61)		(-16.01)		(-6.046)
Post AIA (Implementation) × *Small Firm (p10)*		0.317		-0.969*		-0.265
		(0.564)		(-1.874)		(-0.232)
Large Firm (p90)		1.027***		1.152***		2.128***
		(43.05)		(80.06)		(64.50)

Table 2.6 – Continued from previous page

	Median Quality	*Median Quality*	*High-Quality Patents*	*High-Quality Patents*	*Breakthrough Patents*	*Breakthrough Patents*
	(1)	(2)	(3)	(4)	(5)	(6)
Post AIA (Implementation) × Large Firm (p90)		-0.105*		-0.415***		-0.566***
		(-1.914)		(-13.94)		(-8.428)
Constant	1.531***	0.946***	0.430***	-0.113	-1.057***	-2.192***
	(11.82)	(7.260)	(3.625)	(-1.201)	(-4.160)	(-11.80)
Firm Level Controls as in Table 2.5	Yes	Yes	Yes	Yes	Yes	Yes
Observations	29,821	29,821	29,821	29,821	29,821	29,821
Pseudo R^2	0.141	0.128	0.168	0.155	0.212	0.234

Robust z-statistics in parentheses.

***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$

Table 2.7 Quality of Internal Innovation by Small-sized Firms

This table presents the results illustrating the impact of AIA on patent activity across various small-sized firm groups. It employs a negative binomial model to estimate Equation 2.3. The dependent variables are *Median Quality*, the median KPSS value of patents a firm applied in a given year, *High-Quality Patents*, the number of patents filed by a firm that exceed the median KPSS value for that year, and *Breakthrough Patents*, the number of patents filed by a firm that exceed the 90^{th} percentile KPSS value within the same year. *Post-AIA (Implementation)* is a binary variable that takes the value of one if the year falls after the implementation of the priority rule change in 2013 and zero otherwise. *Small Firm (Median)* is a binary indicator assigned a value of 1 if a firm's total assets are below the median total assets for that year, and 0 otherwise. *Small Firm (p33)* is a binary indicator that takes the value of 1 if the firm's total assets fall below the 33^{rd} percentile in that year, and 0 otherwise. Similarly, *Small Firm (p25)* is a binary indicator that takes the value of 1 if the firm's total assets fall below the 25^{th} percentile in that year, and 0 otherwise. Refer to Appendix A.1 for detailed definitions of the control variables. All continuous variables are winsorized at their 1^{st} and 99^{th} percentiles. All specifications include firm level controls as in Table 2.5, as well as industry-fixed effects. We employ robust standard errors adjusted for heteroscedasticity. t-values are enclosed in parentheses below the reported coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Median Quality	*High-Quality Patents*	*Breakthrough Patents*	*Median Quality*	*High-Quality Patents*	*Breakthrough Patents*	*Median Quality*	*High-Quality Patents*	*Breakthrough Patents*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Post AIA	0.498***	0.241***	0.173***	0.491***	0.261***	0.177***	0.484***	0.261***	0.179***
	(18.13)	(15.52)	(4.565)	(18.74)	(16.20)	(4.545)	(18.59)	(15.90)	(4.573)
Small Firm (Median)	-1.48***	-1.84***	-3.282***						
	(-49.36)	(-66.64)	(-31.23)						
Post AIA	0.0607	0.390***	0.825***						
× *Small Firm (Median)*	(0.922)	(8.091)	(4.750)						
Small Firm (p33)				-1.47***	-1.99***	-3.214***			
				(-44.38)	(-45.78)	(-17.51)			
Post AIA				0.0191	0.271***	0.921***			
× *Small Firm (p33)*				(0.147)	(3.209)	(2.998)			
Small Firm (p25)							-1.42***	-2.02***	-3.181***
							(-36.21)	(-34.73)	(-13.18)

Table 2.7 – Continued from previous page

	Median Quality	*High-Quality Patents*	*Breakthrough Patents*	*Median Quality*	*High-Quality Patents*	*Breakthrough Patents*	*Median Quality*	*High-Quality Patents*	*Breakthrough Patents*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Post AIA							-0.043	-0.027	0.015
× *Small Firm (p25)*							(-0.200)	(-0.199)	(0.0304)
Constant	1.899***	0.747***	-0.059	1.709***	0.591***	-0.225	1.709***	0.575***	-0.244
	(17.08)	(6.674)	(-0.281)	(14.45)	(4.925)	(-1.042)	(14.33)	(4.769)	(-1.131)
Firm Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	30,532	30,532	30,532	30,532	30,532	30,532	30,532	30,532	30,532
Pseudo R^2	0.127	0.156	0.196	0.115	0.129	0.166	0.110	0.117	0.158

Robust z-statistics in parentheses.

***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$

Table 2.8 Replication of Main Results: Excluding Other Legislations

Panels A and B of this table replicate Tables 2.5. and 2.6 using a sample excluding other significant legislations (2000-2018). The dependent variables, including *Patent Applications*, *Days to Grant*, *Median Quality*, *High-Quality Patents*, and *Breakthrough Patents*, mirror those used in Tables 2.3 and 2.4. All regressions control for industry fixed-effects and utilize robust standard errors to account for heteroscedasticity. t-values are displayed in parentheses below the corresponding coefficients, with *, **, and *** indicating statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Patenting Activity

	Patent Applications	*Days to Grant*	*Median Quality*	*High-Quality Patents*	*Breakthrough Patents*
	(1)	(2)	(3)	(4)	(5)
Post AIA	-0.087***	-0.293***	0.079**	-0.140***	-0.487***
	(-3.223)	(-40.40)	(2.423)	(-9.640)	(-14.13)
Size	0.737***	0.0141***	0.439***	0.384***	0.782***
	(112.8)	(7.230)	(41.49)	(101.6)	(73.25)
R&D Intensity	2.422***	-0.125***	-0.662**	0.989***	1.115***
	(18.60)	(-3.222)	(-1.993)	(10.70)	(4.120)
ROA	-0.130**	-0.057***	0.088	0.760***	0.295**
	(-2.314)	(-3.020)	(0.735)	(11.49)	(2.027)
Asset Tangibility	0.682***	-0.183***	-0.145	-0.639***	-0.990***
	(7.441)	(-6.560)	(-1.570)	(-13.59)	(-6.272)
Log (Market-to-Book)	0.240***	0.0416***	0.540***	0.300***	0.759***
	(18.45)	(9.791)	(40.85)	(33.69)	(32.65)
HHI	0.295	0.416***	0.904***	-0.438***	0.506
	(0.790)	(3.854)	(2.684)	(-4.297)	(0.972)
HHI square	-0.515	-0.263**	-1.233***	0.338***	-0.820
	(-1.377)	(-2.319)	(-3.961)	(3.172)	(-1.643)
Market Leverage	-0.428***	-0.133***	-0.415***	-0.221***	-0.871***
	(-8.980)	(-9.061)	(-8.404)	(-7.401)	(-10.22)
Constant	-2.063***	6.535***	-2.118***	-2.592***	-6.702***
	(-13.44)	(96.67)	(-8.680)	(-71.13)	(-25.58)
Industry FEs	Yes	Yes	Yes	Yes	Yes
Observations	18,697	18,697	18,697	18,697	18,697
Pseudo R^2	0.1745	0.0123	0.1691	0.2051	0.3295

Robust z-statistics in parentheses.

***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$

Table 2.8 – Continued from previous page

Panel B. Patenting Activity by Firm Size

	Patent Applications	*Days to Grant*	*Median Quality*	*Breakthrough Patents*
	(1)	(2)	(3)	(4)
Post AIA (implementation)	0.132***	-0.26***	0.412***	-0.0505
	(6.429)	(-30.13)	(14.57)	(-1.356)
Small Firm (Median)	-0.606***	-0.07***	-1.480***	-3.102***
	(-39.24)	(-6.552)	(-53.67)	(-29.41)
Post AIA (implementation)	-0.0446*	-0.06***	0.0320	0.726***
$\times$ *Small Firm (Median)*	(-1.903)	(-3.931)	(0.552)	(4.389)
Constant	5.184***	6.793***	1.950***	0.191
	(24.76)	(125.3)	(8.925)	(0.743)
Observations	17,533	17,533	17,533	17,533
Pseudo R^2	0.0239	0.0114	0.1519	0.2477

Robust z-statistics in parentheses.

***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$

Table 2.9 Falsification Tests: Hypothetical Event Date

This table presents a robustness analysis that replicates the key findings using a hypothetical event year (2004). The dependent variables, including *Patent Applications*, *Days to Grant*, *Median Quality*, and *Breakthrough Patents*, mirror those used in Tables 2.5 and 2.6. *Post (2004)* is a binary variable that takes the value of one if the year falls within the three-year period following 2004 and zero otherwise. All regressions control for industry fixed-effects and utilize robust standard errors to account for heteroscedasticity. t-values are displayed in parentheses below the corresponding coefficients, with *, **, and *** indicating statistical significance at the 10%, 5%, and 1% levels, respectively.

Variables	*Patent Applications* (1)	*Days to Grant* (2)	*Median Quality* (3)	*Breakthrough Patents* (4)
Post (2004)	-0.101	0.0917***	-0.0887	-0.168***
	(-1.590)	(8.447)	(-1.554)	(-3.521)
Small Firm (Median)	-2.449***	-0.0186	-1.635***	-3.381***
	(-36.25)	(-1.142)	(-26.09)	(-16.55)
Post (2004) x Small Firm (Median)	0.0208	-0.00451	-0.145	-0.365
	(0.255)	(-0.230)	(-1.638)	(-1.094)
R&D Intensity	1.735***	-0.0167	0.377	-0.201
	(6.916)	(-0.241)	(1.617)	(-0.364)
ROA	1.017***	0.00133	0.622***	1.870***
	(8.610)	(0.0387)	(5.647)	(6.693)
Asset Tangibility	1.468***	0.0297	1.117***	-0.210
	(6.717)	(0.610)	(5.524)	(-0.773)
Log (Market-to-Book)	0.239***	0.0446***	0.458***	0.632***
	(7.583)	(5.594)	(17.00)	(13.78)
HHI	0.907	0.355	-1.217***	-0.496
	(0.757)	(1.249)	(-3.394)	(-0.396)
HHI square	-1.043	-0.135	1.654***	0.977
	(-0.988)	(-0.493)	(4.245)	(0.849)
Market Leverage	-0.0627	-0.0722***	-0.0754	-0.393**
	(-0.603)	(-2.992)	(-0.802)	(-2.546)
Constant	4.757***	6.576***	1.761***	0.826**
	(14.66)	(87.32)	(17.84)	(2.139)
Observations	5,793	5,793	5,793	5,795
Pseudo R^2	0.1254	0.0111	0.0983	0.2813

Robust z-statistics in parentheses.

***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$

3. SPACs and the Regulation Gap: The Effect of First SEC Intervention on Share and Warrant Returns

3.1 Introduction

Public market access for private companies has traditionally relied on the established Initial Public Offering (IPO) process. However, a recent innovation – the Special Purpose Acquisition Company (SPAC) – has emerged as a viable alternative firms (Chatterjee et al., 2016; Coates, 2022). SPACs, often nicknamed "blank check companies," raise capital through an IPO but lack a specific target company initially. Instead, they use the funds raised to acquire a private company within a set timeframe, typically 18-24 months. This approach effectively takes a private company public through a merger. This alternative path to public listing has gained significant traction, particularly during the global pandemic. In 2020, SPAC IPOs surpassed traditional IPOs for the first time, both in number and total value raised (Gahng et al., 2023). Despite this growing popularity, the academic landscape concerning the advantages and disadvantages of SPACs remains relatively unexplored.[1]

Concerns center around the potential for lower quality companies to access public markets through SPAC mergers (Bai et al., 2021; Floros and Sapp, 2011; Gryglewicz et al., 2022; Kolb and Tykvová, 2016). Critics view SPACs as a "back door" bypassing stricter IPO requirements (Chatterjee et al., 2016), potentially facilitated by a perceived lack of regulatory oversight (Klausner et al., 2022; Rodrigues and Stegemoller, 2021; Wen and Zhu, 2022). Industry professionals echo these concerns, suggesting the SPAC boom is fueled by "regulatory arbitrage," anticipating stricter regulations in the future (Aliaj and Kruppa, 2021; Aliaj, 2021). Even regulatory bodies acknowledge being surprised by the volume of SPAC activity and hint at potential adjustments to address the perceived advantages SPACs currently enjoy (U.S. Securities and Exchange Commission, 2021a). Furthermore, concerns exist regard-

[1] Recent studies in the growing SPAC literature include Cumming et al. (2014), Blomkvist and Vulanovic (2020), and Papathanasiou et al. (2021).

ing the potential for unequal distribution of benefits, with unsophisticated investors potentially bearing the brunt of risks associated with lower-quality companies.[2]

The surge in popularity of Special Purpose Acquisition Companies (SPACs) has been attributed to a perceived regulatory gap. However, concrete regulatory action was delayed until April 12, 2021, when the Securities Exchange Commission (SEC) issued a directive reclassifying SPAC warrants as liabilities on balance sheets, effectively altering the financial reporting of most SPACs (U.S. Securities and Exchange Commission, 2021c). This landmark decision, marking the beginning of potentially broader regulatory efforts, holds significant implications beyond its immediate impact. This paper investigates the effect of this SEC announcement on all active SPACs between 2018 and 2021 using an event-study methodology. By analyzing the financial performance of SPACs before and after the SEC's directive, we aim to assess the extent to which this regulatory change influenced the SPAC market.

While the regulatory changes themselves did not directly impact SPACs' cash reserves, the necessary adjustments could strain companies financially due to the time, resources, and legal/accounting fees required. The announcement's impact on SPAC stock prices offers a crucial insight into the industry's value proposition. If the industry's success is solely based on its regulatory advantages over traditional IPOs, the announcement could trigger a significant decline in average SPAC stock prices, reflecting investor concerns about future regulatory adjustments. Conversely, if some investors are indeed profiting from a regulatory loophole, the SEC's intervention could be viewed as a positive governance move, potentially leading to increased returns for SPAC companies.

This study investigates the impact of the SEC's initial statements regarding SPACs on the performance of SPAC shares and warrants. We conducted analyses using both the Market Model (MM) and the Mean-Adjusted Model (MAM) over 3- and 7-day event windows. Initial findings indicate no statistically significant impact on SPAC share or warrant prices around the time of the SEC's first official statements. However, further exploration using multivariate regressions revealed that individual SPAC characteristics influence unit/share returns. Contrary to expectations, SPACs with warrants in their units did not demonstrate significantly lower performance. In fact, some evidence suggests they may even benefit from the regulation. This potential benefit might stem from investor perception that regulatory oversight is

[2] While traditional IPOs are subject to strict regulations, SPACs enjoy a unique legal shield. This "safe harbor" provision allows private companies merging with SPACs to make projections about their future performance without fear of immediate legal repercussions. However, research by Dambra et al. (2023) and Blankespoor et al. (2022) suggests that this leniency can be exploited. These studies indicate that some SPAC targets may leverage the safe harbor to paint overly optimistic financial pictures, potentially misleading investors. This is especially detrimental to less experienced investors, who may struggle to identify and assess the risks associated with such projections.

beneficial for both current and future investors, fostering confidence in the evolving SPAC industry. Furthermore, the analysis identified factors associated with poorer performance: larger SPACs, those with shorter time to expiration, and those specifying a specific industry for acquisitions. These findings suggest that investors may value the agility and flexibility provided by smaller SPACs, especially in a potentially shifting regulatory environment. This flexibility allows for quicker, potentially less costly adjustments to meet changing market conditions. These results provide valuable insights into the impact of SEC regulation on SPACs and highlight the importance of considering individual SPAC characteristics in predicting their performance.

3.2 The SPAC Process and SEC Statements on SPACs

3.2.1 The SPAC Process

Special Purpose Acquisition Companies (SPACs), also known as "blank check companies," are a recent innovation in the world of taking companies public. Unlike traditional IPOs, where a specific company raises capital, SPACs are essentially shell companies that raise money through an IPO with the only purpose of acquiring another, private firm. These "blank check" funds typically sell units to investors at a set price (often $10). Each unit is a combination of a common share and a warrant. The warrant grants the holder the right to buy an additional share at a predetermined price (e.g., $11.50) within a specific timeframe. These warrants can be exercised on the later of 12 months from the IPO or 30 days following the merger, expiring five years after the merger. Units can be separated and traded individually 52 days after the IPO. The proceeds generated through the IPO are placed in an interest-bearing trust account; thereafter the search process for an appropriate target firm for merger starts.

Unlike traditional IPOs, SPACs don't disclose a specific target during their offering. They might, however, indicate a general area of interest (e.g., industry or geography). There's no limit on the target's size, but the acquisition must utilize at least 80% of the funds in the trust. SPACs typically have a time limit (18-24 months) to find and merge with a target, although some offer investors a vote to extend this period. If a suitable merger partner is identified, a shareholder vote is held to approve the deal. With enough votes in favor, the SPAC merges with the target, and the combined entity becomes a publicly traded company under the target's name. Dissenting shareholders can redeem their shares for the original purchase price plus interest. However, if the merger fails to gain shareholder approval, then the SPAC has two options: liquidation or continuing the search for a new target. In case of liquidation, the funds in the trust (including interest) are distributed to shareholders. SPACs are often headed by experienced investors who act as sponsors. These sponsors receive a significant ownership stake (usually 20%) in the target company after a successful merger, in exchange for their efforts in forming and managing the SPAC. However, if no merger materializes, the sponsors receive no compensation.

3.2.2 The Securities and Exchange Commission (SEC) Public Statements on SPACs

The surge in popularity of SPACs in 2021 prompted the Securities and Exchange Commission (SEC) to initiate a comprehensive examination of the industry. This scrutiny was publicly manifested through a series of statements, culminating in regulatory action. The SEC's initial public pronouncements on March 31$^{\text{st}}$ and April 8$^{\text{th}}$, 2021, aimed to educate investors on the intricacies of SPACs (U.S. Securities and Exchange Commission, 2021b). The agency highlighted the unique structure and mechanics of these vehicles, emphasizing both the potential rewards and inherent risks. These statements served as a cautionary message, particularly for retail investors drawn to the perceived simplicity of SPAC investing. On April 8$^{\text{th}}$, the SEC's acting director of Corporate Finance, John Coates, drew parallels between SPAC mergers (de-SPAC process) and traditional Initial Public Offerings (IPOs) (U.S. Securities and Exchange Commission, 2021a). Mr. Coates suggested that similar regulatory frameworks should be applied to both, underscoring the SEC's commitment to ensure a level playing field for investors.

The SEC's most impactful intervention came on April 12$^{\text{th}}$. In a landmark decision, the agency mandated that warrants issued by SPACs be classified as liabilities rather than equities on company balance sheets (U.S. Securities and Exchange Commission, 2021c). This reclassification significantly altered accounting practices for SPACs, impacting earnings reporting as warrant values are now subject to fair value adjustments. The ramifications extended beyond accounting, as warrants, a key driver of potential returns for investors, were now viewed as a cost factor. While redemption rights protected investors against downside risk, warrants had played a critical role in amplifying potential gains (Ramkumar, 2021).

This regulatory shift sent shockwaves through the SPAC market, prompting a dramatic slowdown in SPAC IPOs (Maurer, 2021). Market participants perceived the SEC's actions as an attempt to curb the rapid expansion of the industry, prompting extensive discussion within the financial press, accounting, and legal communities (Bertoni and Gara, 2021; Michaels et al., 2021).

The SEC's April 12$^{\text{th}}$ statement mandated financial statement restatements and mandated Form 8-K filings for all SPACs. A subsequent analysis of SEC filings on EDGAR revealed that, with a few exceptions, the SEC's directive had demonstrably impacted the vast majority of SPACs, underscoring the tangible consequences of its regulatory intervention. An analysis of these filings on EDGAR confirmed the tangible impact of the SEC's intervention on the SPACs in our sample.

3.3 Data and Empirical Methodology

3.3.1 Sample Formation

This study utilizes data from SPAC Insider, a database providing detailed information on these unique investment vehicles. To ensure data accuracy, we meticulously cross-referenced information with publicly available S-1 filings on the SEC's EDGAR system. We found no discrepancies. Our analysis covers 1,180 SPACs initiated in the U.S. between January 2010 and August 2021. By the end of the sample period, these SPACs had transitioned through various stages: 430 SPACs remained actively seeking suitable acquisition opportunities; 146 SPACs had announced a merger or acquisition agreement; 266 SPACs successfully completed a business combination, merging with target companies; 312 SPACs were in the final stages of completing their IPO paperwork; and 26 SPACs were liquidated, failing to find suitable merger targets.

Panel A of Table 3.1 highlights the remarkable surge in SPAC IPO activity over the years. Since 2010, both the quantity and average size of SPACs have grown exponentially, with this trend accelerating significantly after the COVID-19 outbreak. In 2021 alone, the total value of the SPAC market reached an unprecedented 105 billion USD. The average SPAC raised 267 million USD from investors. This significant surge has sparked discussions within the corporate finance community regarding the long-term viability of SPACs as an alternative to traditional IPOs (Gahng et al., 2023; Galbraith et al., 2021; Klausner et al., 2022; Klausner and Ruan, 2021).

To construct our dataset including the period surrounding the SEC's statements (04/2020 - 04/2021), we collect daily price data for SPACs. We utilize a combination of sources: Yahoo Finance and The Wall Street Journal. This price data is then combined with information from SPAC Insider, resulting in a final dataset of 551 observations.

3.3.2 Empirical Methodology

We investigate the market reaction to the implementation of a specific SEC regulation concerning SPACs. To evaluate the impact of the SEC regulation on market reaction, we conducted an event study analysis (Brown and Warner, 1985). To establish a benchmark for expected stock returns, two distinct models are employed: the Market Model (MM) and the Mean-Adjusted Model (MAM). MM model assumes a stock's return is linked to the overall market performance (e.g., S&P 500). We estimate the historical relationship between a SPAC's return and the market return during a pre-event window (i.e., the intercept α_i and the slope β_i) to predict its expected return during the event window (typically defined around the announcement date). Mean Adjusted Model is a simpler model, assuming a SPAC's expected return is equal to its average historical return during the pre-event window.

For both models, the pre-event window spans from 125 days before the announcement day of April 12$^{\text{th}}$ (day zero) to 2 days before (denoted as -125 to -2). We require at least 30 data points within this window for reliable parameter estimation, resulting in a final sample of 401 SPACs. We construct cumulative abnormal returns (CARs) to capture the market's overall response to the SEC announcement. This involves summing the daily abnormal returns, calculated as the difference between actual security returns and expected returns estimated using both the Market Model (MM) and the Mean-Adjusted Model (MAM) (Brown and Warner, 1985). We analyze two event windows: one spanning one day before and one day after the announcement (-1, +1), and another extending to five days after (-1, +5). The shorter window isolates the immediate market reaction, while the longer window allows us to assess the persistence of the effect over several days. To address potential biases arising from overlapping event windows and cross-sectional correlations among security returns, we utilize two established test statistics, the Adjusted Patell (ADJPatell) and the Kolari and Pynnonen (KP) tests, to evaluate the statistical reliability of our Cumulative Abnormal Return estimates. (Kolari et al., 2018; Kolari and Pynnönen, 2010). These adjustments mitigate the likelihood of falsely rejecting the null hypothesis of zero average abnormal returns.

We further utilize a regression model incorporating various independent variables to explain cross-sectional variations in SPAC CARs. These variables are detailed in Table 3.1, which highlights key characteristics of the SPAC sample. As Panel B of Table 3.1 indicates, 95% of the SPACs include some fraction of warrant in their units. The capital raised through IPOs varies significantly, ranging from \$40 million to \$4 billion. The average SPAC raises \$285 million. The average time remaining for SPACs to complete their acquisitions (17.5 months) suggests most are in the early stages of their lifecycles. Over 90% of SPACs target specific sectors or geographical regions for their acquisitions. Almost half (45%) of SPACs rely solely on individual sponsors for financing.

3.4 Empirical Results

3.4.1 SPAC Market Response to the SEC's Accounting Guidance on Warrants (April 12$^{\text{th}}$)

Table 3.2 Panel A examines the average cumulative abnormal returns (CARs) for SPAC shares surrounding the SEC's announcement regarding accounting treatment for warrants on April 12$^{\text{th}}$. We calculate CARs for two event windows: (-1, +1) and (-1, +5). The results show an average decline of -0.54% and -1.6% While these figures might suggest a potentially meaningful market response compared to typical corporate events (e.g., mergers and acquisitions, dividend announcements, or share repurchases), they lack statistical significance. This can be attributed to the substantial variation in abnormal returns across different SPACs and over time. Employing both the Adjusted Patell and KP tests confirm this lack of significance, as evidenced by high p-values. Additionally, using the Mean-Adjusted Model (MAM) for calculating abnormal returns yielded similar findings.

While share prices showed a muted response, the impact on SPAC warrants appears more pronounced (Table 3.2 Panel B). The average decline in warrant value was -6.3% in the short term (1 day before to 1 day after) and -16.1% in the extended window (1 day before to 5 days after) the SEC statement. However, despite these seemingly large drops, they are not statistically significant for the short-term window. Only the extended window's decline reaches borderline significance according to the KP test. This lack of definitive statistical evidence can again be attributed to the inherent volatility of warrant returns, making it difficult to isolate the SEC announcement's specific effect. Similar results were obtained using an alternative method (MAM) to calculate abnormal returns. The larger declines in warrants compared to shares align with the inherent risk associated with warrants, as discussed in (Gahng et al., 2023).

3.4.2 SEC Statement (April 12th): Market Reactions and Influencing Factors

To examine potential relationships between SPAC characteristics and returns, we conduct a multiple regression analysis. Our study focuses on cumulative abnormal returns (CARs) calculated using the Market Model around April 12th, 2021, for SPAC shares. The primary analysis utilizes Cumulative Abnormal Returns measured over a (-1, +1) event window, with additional analysis using a (-1, +5) event window. The independent variables in our model include *warrant ratio*, *log(SPAC proceeds)*, *months until completion*, *industry-constrained* and *non-institutional*. A detailed explanation of how these variables were constructed can be found in Table 3.1. Table C.1 in the Appendix presents a summary of potential effects these variables may have on the dependent variable.

Our regression analysis, displayed in Table 3.3, revealed a positive relationship between warrant ratio and SPAC performance during the SEC announcement period. This suggests that SPACs with warrants in their units tended to outperform those without warrants. However, the significance of these coefficients varied across regressions, preventing us from confidently concluding a causal effect of *warrant ratio* on SPAC performance.

Our analysis reveals an inverse relationship between SPAC proceeds and CARs during the event window. Larger SPACs, as indicated by the statistically significant negative coefficient for the *log(SPAC proceeds)* variable, tend to exhibit lower CARs. Specifically, in column (5), a ten percent increase in SPAC proceeds is associated with a 7.4 basis point decrease in CARs. This finding suggests that larger SPACs, with their wider investor base, may face greater adjustment costs, potentially contributing to their lower returns.

Our findings suggest a positive relation between time remaining until SPAC deal completion and CARs. SPACs with longer deadlines, specifically those with an additional 5.1 months (representing one standard deviation increase), exhibited a 51 basis point increase in CARs compared to those facing imminent completion. This suggests that newly established SPACs with extended deadlines may benefit from increased flexibility in navigating potential regulatory changes. However, the analysis revealed no significant impact from industry-specific or non-institutional characteristics on CARs.

Expanding the analysis to a (-1, +5) window for cumulative abnormal returns (CARs) in column (6), we observe a change in the significance of certain variables. While warrant ratio no longer shows a statistically significant effect, SPACs focused on particular industries are demonstrably worse off. This suggests that the SEC statement may negatively impact industry-specific SPACs, potentially because of a lower flexibility in selecting merger partners, as their search pool is limited to a narrower set of targets.[3]

3.4.3 Anticipation Effect: CARs around Prior SEC Press Releases

We next investigate whether the prior press releases of the SEC absorbed the possible impact of the official announcement on 12^{th}. The initial SEC statements on March 31^{st} and April 8^{th} may signal forthcoming regulations to the SPAC industry; hence, investors may react to these events prior to the main SEC statement on April 12^{th}. To explore this possibility, we repeat our event study analysis around these two dates. Panel A of Table 3.4 reports the average CARs to SPAC shares that are estimated with the MM method. The average CARs during the (-1, +1) periods are 0.25% for the March 31^{st} communication and 0.5% for the April 8^{th} communication. Neither estimate is statistically different from zero. Panel B shows the average CARs to warrants around March 31st and April 8^{th}. The mean CARs estimated around March 31^{st} is -2.09% while the mean CARs for April 8^{th} is 3.94%. However, none of the estimates is statistically significant according to the Adjusted Patell and KP tests. In addition, we also check abnormal returns around May 24, 2021, when the U.S. House Committee on Financial Services released a draft legislation

[3] To assess market anticipation, we conducted additional regressions using Cumulative Abnormal Returns calculated around the earlier SEC announcements on March 31^{st} and April 8^{th}. The announcement on April 8^{th}, that first introduced the concept of a "regulation gap," yielded marginally similar results to our baseline regressions. However, the analysis of the March 31^{st} announcement did not reveal comparable effects.

suggesting that SPACs should be excluded from safe harbor protection, directly aimed at reducing regulatory arbitrage. We again find no statistically significant effects.

3.4.4 The Cumulative Effect of all SEC statements

To capture a potentially cumulative effect of all three SEC statements on share and warrant prices, we construct a longer event window starting from the March 31st announcement and ending at the April 12th announcement. Panels A and B in Table 3.4 show the average CARs to SPAC shares and warrants (respectively) estimated over the longer (-9, +1) window. Average CAR to shares is -0.01% over this longer event window, while the average CAR to warrants is 3.45% over the same window. Again, both figures are statistically insignificant.

3.4.5 The Possible Effects of Other Events

SPACs tend to generate positive abnormal returns in the days following an announcement of a merger partner (Boyer and Baigent, 2008; Dimitrova, 2017; Howe and O'Brien, 2012; Lakicevic and Vulanovic, 2013; Rodrigues and Stegemoller, 2014). To eliminate the possible effects of these events on our estimations, as a robustness check, we drop the SPACs that announced a merger less than five days before April 12th and re-run our tests. Only five SPACs in our sample had such announcements. As Table 3.5 shows, excluding those SPACs from our sample does not change the main conclusions from our analyses. The results remain similar with those reported in Table 3.2.

3.4.6 Alternative Estimation Window

We estimate the expected returns in the MM approach over an alternative estimation window of (-250, -2). In addition, we estimate CARs over alternative event windows, such as (-2,+2), (-5,+5), and (-1,+2). The results under these alternative specifications remain unchanged. We also estimate a market-adjusted model, where market returns are subtracted from security returns over the estimation and event windows. Our results continue to hold under this specification as well.

3.4.7 CARs with SPAC Shares

We assess the impact of our security price data handling method on our results. If there is security return data for both SPAC units and shares, we ignore unit returns and use share returns in our baseline calculations. If share returns are missing (e.g., the period before the unit splits into shares and warrants), we import unit returns for the missing parts of the share returns, based on the observation that share and unit returns are highly correlated. We follow this strategy to obtain a higher sample size, however, the results remain unchanged if we drop this assumption and do not use unit returns for the missing share returns.

3.4.8 Alternative "Warrant Ratio" Measures

The sample size of the control group for warrant ratio in baseline regressions reported in Table 3.3 is too small: only 19 out of 401 SPACs have zero warrant ratios. To ensure that our results are robust to the definition of this variable, we had created alternative warrant ratio variables and re-run our tests using these alternative versions. We had noticed that the distribution of warrant ratios is highly clustered. As Figure 3.1 shows, 69% of the SPACs contain either one-half or one-third of a warrant in their unit. Table 3.6 shows that the median level of the warrant ratio is one-third, while the mean is 0.40. Given the highly clustered distribution of warrant ratios, we had decided not to use the continuous version of the warrant ratio variable in our regression analyses.

Therefore, we introduce the continuous version of the warrant ratio variable (*warrant ratio (continuous)*) and two alternative '*high warrant ratio*' indicator variables, which do not suffer from the low sample size issue for the control group. These alternative indicator variables are: (i) *high warrant ratio (mean)*, which equals one if warrant ratio is greater than or equal to the mean, and zero otherwise, and (ii) *high warrant ratio (median)*, which equals one if warrant ratio is greater than or equal to the median level of 0.33, and zero otherwise. Distributional features of these three warrant ratio variables are reported in Table 3.6. The main results are robust to repeating the regressions using these alternative dummy variables. Panels A, B and C of Table 3.7 replaces the original *warrant ratio* variable in Table 3.3 with *warrant ratio (continuous)*, *high warrant ratio (mean)* and *high warrant ratio (median)*, respectively. The three alternative warrant ratio ratios attain mostly positive coefficients, and these coefficients are usually statistically significant at the 10% level in Panels A and B. Except for one case, the positive coefficients of the *high warrant ratio (median)* are not statistically significant in Panel C.

Taken as a whole, the results show that whether firms simply have a warrant in their SPAC units or have 'high warrant ratio' based on the mean or the median warrant ratio in cross-section, they do not appear to be disadvantaged due to the SEC regulation, when compared to their counterparts with either zero or less than mean or median warrant levels. Despite the SEC's targeting warrants directly, investors do not seem to perceive the SEC statement negatively for these types of firms. In fact, there is some evidence that market perceives the SEC intervention positively for firms with warrant ratio.

3.4.9 The Impact of Pre-Announcement Mergers on SPAC Performance

One potential concern is that SPACs which announced mergers before the SEC announcement (early announcers) might have already benefited from presenting overly optimistic projections. These companies could be less affected by the regulation compared to SPACs still searching for targets at the time of the announcement (late announcers). They wouldn't have the same incentive to make overly optimistic projections knowing the SEC is scrutinizing them. To explore this, we divided our sample based on whether a merger was announced before the SEC announcement. Table 3.8 shows the average cumulative abnormal returns for SPAC shares near April 12$^{\text{th}}$, calculated separately for early and late announcers. While our initial analysis suggests that early announcers might have performed worse, these results lack statistical significance. We further investigated this by including a dummy variable in our regression analysis to account for pre-announcement mergers. When controlling for other SPAC characteristics in the shorter (-1, +1) window, we don't find a significant difference between the two groups.

3.5 Conclusion

This study employs event-study methodology to investigate the effect of the first official SEC announcement concerning SPACs. The prevailing notion suggests that regulatory arbitrage is the cornerstone of SPACs' attractiveness. Therefore, a negative impact from the initial regulatory intervention on this mechanism was anticipated. However, our findings challenge this expectation. While the overall results are not consistent with the predicted decline, specific SPAC characteristics exhibit statistically significant negative associations with stock returns. These characteristics include high initial public offering (IPO) proceeds, limited time remaining until deal deadline, and predetermined industry focus. Larger capital raises might have been perceived as less efficient or indicative of potentially weaker target acquisition prospects. SPACs with shorter timeframes for completing a merger might have raised concerns about their ability to identify and secure a suitable target before the deadline. Specifying a target industry in advance could limit the pool of potential acquisition candidates, potentially reducing investor confidence. Interestingly, despite the SEC announcement directly targeting warrant accounting, SPACs with warrants experienced modestly higher returns. This suggests that some investors may have viewed the regulatory intervention positively, potentially due to increased clarity and standardization in the warrant accounting process. This analysis offers valuable insights into market reactions to regulatory developments regarding SPACs. While the overall impact of the announcement wasn't a decline as anticipated, specific SPAC features significantly influenced investor responses.

3.6 Tables and Figures

Figure 3.1 The Cross-Sectional Distribution of Warrant Ratio (Percent of Warrants Included in One SPAC Unit)

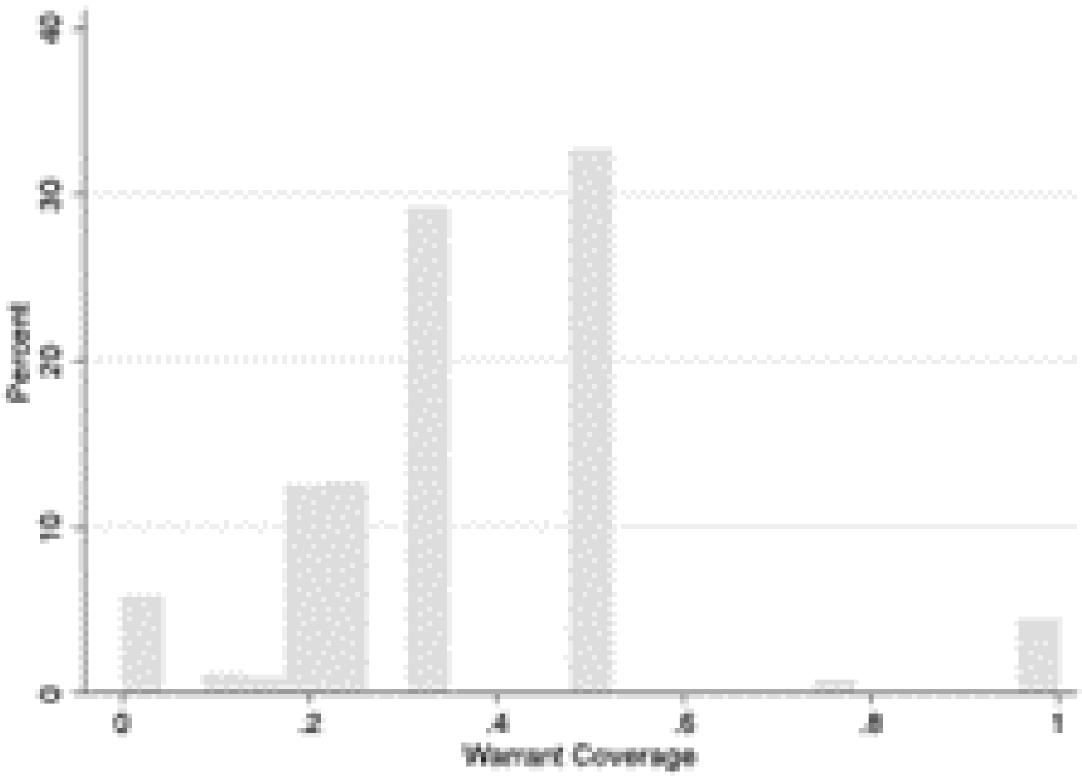


Table 3.1 Summary Statistics

This table displays key characteristics of the SPACs, covering the period from 2010 to 2021. Panel A details the quantity of SPAC initial public offerings, alongside the total and average public proceeds raised during this timeframe. Panel B provides an overview of the control variables employed in the subsequent regression analysis. The sample includes 401 SPACs. Among these, 64 had completed a merger by April 12. *warrant ratio* is a binary variable that takes a value of 1 if a SPAC's unit composition includes any warrant ratio, and 0 otherwise. *SPAC Proceeds* represents the proceeds raised from public investors through the initial public offering (in millions of dollars). *months until completion* captures the number of months between the SPAC's merger completion deadline and announcement made on April 12. *industry-constrained* is a binary variable that takes a value of 1 if a SPAC prioritizes specific industries or geographic regions for its target acquisition, and 0 otherwise. *non-institutional* is a binary variable that takes a value of 1 if the sponsor type is an individual, and 0 otherwise.

Panel A. Trends in SPAC Filings Over Time

Year	*Number of SPACs*	*Total Volume of SPACs (Million USD)*	*Mean SPAC proceeds (Million USD)*
2010	7	491	70.1
2011	15	1,024.5	68.3
2012	9	475	52.8
2013	10	1,324.8	132.5
2014	12	1,590	132.5
2015	20	3,612	180.6
2016	13	3,224	248.0
2017	34	8,995.5	264.6
2018	46	9,685	210.5
2019	59	12,089	204.9
2020	248	75,587.6	304.8
2021	395	105,555	267.2

Table 3.1 – Continued from previous page

Panel B. Data Summary

	N	*Mean*	*Median*	*Minimum*	*Maximum*	*Standard Deviation*
warrant ratio	401	0.95	1	0	1	0.21
SPAC Proceeds	401	283.89	240	40	4,000	257.8
months until completion	337	17.50	19.2	4.0	22.4	5.1
industry-constrained	401	0.91	1	0	1	0.28
non-institutional	401	0.45	0	0	1	0.50

Table 3.2 Market Response to SEC's Accounting Treatment for SPACs

This table presents the average cumulative abnormal returns (CARs) for both SPAC shares (Panel A) and warrants (Panel B) surrounding the SEC's public announcement on April 12^{th} public statement. We calculate CARs using two event windows: 3-day and 7-day windows. The abnormal returns are estimated using both the Market Model (MM) and the Mean-Adjusted Model (MAM) to account for potential market effects. The standard errors for all models are calculated using established methods, including the Adjusted Patell and the Kolari and Pynnonen (KP) approaches.

Panel A. SPAC Share Performance around April 12^{th}, 2021

	N	Mean	Adjusted Patell Test p-val.	KP Test p-val.
CAR (-1,+1) Market Model	401	-0.54%	(0.900)	(0.861)
CAR (-1,+5) Market Model	401	-1.60%	(0.700)	(0.535)
CAR (-1,+1) Mean Adj. Model	401	-0.27%	(0.897)	(0.858)
CAR (-1,+5) Mean Adj. Model	401	-1.34%	(0.875)	(0.803)

Panel B. SPAC Warrant Performance around April 12^{th}, 2021

	N	Mean	Adjusted Patell	KP
CAR (-1,+1) Market Model	170	-6.30%	(0.312)	(0.151)
CAR (-1,+5) Market Model	170	-16.15%	(0.128)	(0.029)**
CAR (-1,+1) Mean Adj. Model	170	-4.41%	(0.559)	(0.410)
CAR (-1,+5) Mean Adj. Model	170	-14.36%	(0.283)	(0.130)

Table 3.3 Factors Influencing Cumulative Abnormal Returns Calculated Around the SEC Statement on April 12th

This table presents the results of Ordinary Least Squares regressions. Columns (1) to (5) examine the cumulative abnormal returns estimated over a three-day window centered on April 12th, using the MM as the benchmark.The dependent variable in each of these columns is the CAR. Column (6) utilizes the same model specification as column (5), but the dependent variable is replaced with the cumulative abnormal return estimated over a wider window of (-1, +5) days surrounding the announcement. A detailed description of the explanatory variables can be found in Table 3.1. The table employs robust standard errors, presented in parentheses. *, **, and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	CAR	CAR	CAR	CAR	CAR	CAR
	(-1, +1)	(-1, +1)	(-1, +1)	(-1, +1)	(-1, +1)	(-1, +5)
	(1)	(2)	(3)	(4)	(5)	(6)
warrant ratio	0.005	0.006	0.007*	0.007*	0.008**	0.006
	(0.007)	(0.007)	(0.004)	(0.003)	(0.004)	(0.007)
log(SPAC proceeds)		-0.004**	-0.007***	-0.007***	-0.007***	-0.016***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
months until completion			0.001***	0.001***	0.001***	0.002***
			(0.000)	(0.000)	(0.000)	(0.000)
industry-constrained				-0.002	-0.002	-0.011***
				(0.002)	(0.003)	(0.004)
non-institutional					-0.003	0.004
					(0.002)	(0.004)
Constant	-0.010	0.013	0.014	0.017	0.019*	0.047***
	(0.006)	(0.012)	(0.009)	(0.011)	(0.010)	(0.015)
N	401	401	337	337	337	337
R^2	0.001	0.011	0.036	0.037	0.043	0.073

Table 3.4 Market Reaction to SPAC Shares and Warrants around prior SEC Statements

This table presents the average cumulative abnormal returns (CARs) for SPAC shares (Panel A) and warrants (Panel B). These are estimated using the MM over two event windows: 3 days and 11 days surrounding the announcements on March 31st, April 8th and April 12th. To ensure robust standard error estimates, both the Adj. Patell and KP methods were implemented in the analysis of all models.

Panel A. SPAC shares around alternative dates

	N	Mean	Adj. Patell	KP
CAR (-1,+1) - March 31st, 2021	369	0.25%	(0.897)	(0.844)
CAR (-1,+1) - April 8th, 2021	395	0.50%	(0.440)	(0.509)
CAR (-9,+1) - April 12th, 2021	401	-0.01%	(0.618)	(0.781)

Panel B. SPAC warrants around alternative dates

	N	Mean	Adj. Patell	KP
CAR (-1,+1) - March 31st, 2021	168	-2.09%	(0.697)	(0.599)

CAR (-1,+1) - April 8^{th}, 2021	172	3.94%	(0.711)	(0.753)
CAR (-9,+1) - April 12^{th}, 2021	170	3.45%	(0.846)	(0.880)

Table 3.5 Factors Influencing Cumulative Abnormal Returns Calculated Around the SEC Announcement- Excluding Other Events

This table reports the results of OLS regressions. The dependent variables are the Cumulative Abnormal Returns for a 3-day event window surrounding the SEC announcement on April 12^{th}, employing the Market Model for estimation. The construction of explanatory variables are provided in Table 3.1. SPACs that announced a merger less than five days before and a day after April 12^{th} are excluded from the original sample.

	CAR (-1, +1)	CAR (-1, +1)	CAR (-1, +1)	CAR (-1, +1)	CAR (-1, +1)
warrant ratio	0.004	0.006	0.006	0.006	0.007*
	(0.00692)	(0.00688)	(0.00406)	(0.00406)	(0.00422)
log(size)		-0.005***	-0.007***	-0.007***	-0.007***
		(0.00182)	(0.00209)	(0.00226)	(0.00215)
months until completion			0.001***	0.001***	0.001***
			(0.000249)	(0.000249)	(0.000248)
industry-constrained				-0.003	-0.002
				(0.00239)	(0.00256)
non-institutional					-0.003
					(0.00227)
Constant	-0.009	0.014	0.016*	0.021*	0.023**
	(0.00678)	(0.0117)	(0.00899)	(0.0112)	(0.0105)
Observations	396	396	333	333	333
R^2	0.001	0.012	0.040	0.042	0.047

Table 3.6 Data Summary for Alternative Warrant Ratio Measures

This table provides summary statistics for the alternative warrant ratio variables. *warrant ratio (continuous)* measures the percent of warrants in a SPAC unit. *high warrant ratio (mean)* takes a value of one if the warrant ratio (percent of warrants in a SPAC unit) is greater than the mean warrant ratio for all SPACs in our sample, which is 0.40. *high warrant ratio (median)* takes a value of one if the warrant ratio (percent of warrants in a SPAC unit) is greater than the median warrant ratio for all SPACs in our sample, which is 0.33.

	N	*Mean*	*Median*	*Min*	*Max*
warrant ratio (continuous)	401	0.40	0.33	0	1
high warrant ratio (mean)	401	0.47	0	0	1
high warrant ratio (median)	401	0.75	1	0	1

Table 3.7 Determinants of CARs with Alternative Warrant Ratio Measures

This table reports the results of OLS regressions. The dependent variables are the CARs estimated over a period of three-day event window around April 12th, using the Market Model. The construction of the explanatory variables is summarized in Table 3.1. The regression is identical to those reported in Table 3.3, except that in Panels A, B and C *warrant ratio* is replaced with *warrant ratio (continuous)*, *high warrant ratio (mean)* and *high warrant ratio (median)*, respectively. *warrant ratio (continuous)* measures the percent of warrants in a SPAC unit. *high warrant ratio (mean)* takes the value of one if warrant ratio is greater than or equal to the mean level of 0.40 while *high warrant ratio (median)* takes the value of one if warrant ratio is greater than or equal to the median level of 0.33, and zero otherwise.

Panel A. Alternative definition of warrant ratio - 1

	CAR (-1,+1)	*CAR (-1,+1)*	*CAR (-1,+1)*	*CAR (-1,+1)*	*CAR (-1,+1)*
warrant ratio (continuous)	0.0007	-0.0056	0.0113*	0.0115*	0.0141**
	(0.0078)	(0.0093)	(0.0059)	(0.0059)	(0.0066)
log(SPAC proceeds)		-0.0049**	-0.0052**	-0.0055**	-0.0056**
		(0.0024)	(0.0021)	(0.0023)	(0.0022)
months until completion			0.0010***	0.0010***	0.0010***
			(0.0003)	(0.0003)	(0.0003)
industry-constrained				-0.0026	-0.0021
				(0.0024)	(0.0025)
non-institutional					-0.0038
					(0.0024)
Constant	-0.0060*	0.0235	0.0049	0.0087	0.0090
	(0.0032)	(0.0154)	(0.0111)	(0.0127)	(0.0126)
Observations	401	401	337	337	337
R^2	0.000	0.010	0.039	0.040	0.047

Table 3.7 – Continued from previous page

Panel B. Alternative definition of warrant ratio - 2

	CAR (-1,+1)	*CAR (-1,+1)*	*CAR (-1,+1)*	*CAR (-1,+1)*	*CAR (-1,+1)*
high warrant ratio (mean)	0.00135	-0.00121	0.00506*	0.00510*	0.00578*
	(0.00275)	(0.00330)	(0.00301)	(0.00302)	(0.00321)
log(SPAC proceeds)		-0.00460**	-0.00485**	-0.00514**	-0.00526**
		(0.00230)	(0.00218)	(0.00234)	(0.00231)
months until completion			0.000957***	0.000957***	0.000969***
			(0.000273)	(0.000274)	(0.000273)
industry-constrained				-0.00248	-0.00202
				(0.00242)	(0.00256)
non-institutional					-0.00351
					(0.00237)
Constant	-0.00633***	0.0199	0.00538	0.00916	0.0105
	(0.00158)	(0.0130)	(0.0107)	(0.0126)	(0.0121)
Observations	401	401	337	337	337
R^2	0.001	0.009	0.041	0.042	0.048

Table 3.7 – Continued from previous page

Panel C. Alternative definition of warrant ratio - 3

	CAR (-1,+1)	*CAR (-1,+1)*	*CAR (-1,+1)*	*CAR (-1,+1)*	*CAR (-1,+1)*
high warrant ratio (median)	0.00320	0.00163	0.00415	0.00443	0.00535*
	(0.00305)	(0.00324)	(0.00296)	(0.00300)	(0.00321)
log(SPAC proceeds)		-0.00379*	-0.00542**	-0.00575**	-0.00591***
		(0.00200)	(0.00216)	(0.00230)	(0.00226)
months until completion			0.000843***	0.000846***	0.000848***
			(0.000250)	(0.000251)	(0.000249)
industry-constrained				-0.00309	-0.00274
				(0.00245)	(0.00254)
non-institutional					-0.00366
					(0.00236)
Constant	-0.00810***	0.0138	0.00975	0.0140	0.0156
	(0.00261)	(0.0118)	(0.0105)	(0.0120)	(0.0115)
Observations	401	401	337	337	337
R^2	0.003	0.009	0.038	0.040	0.046

Table 3.8 Market Reaction to SPAC Shares: SPACs with Announced Deals vs. SPACs without Deals

This table presents the average cumulative abnormal returns of SPAC shares using the Market Model over 3- and 7-day event windows surrounding SEC announcement on April 12th. The data is broken down by SPACs that had announced a deal before the statement and those that had not. Standard errors in all models are calculated using the Adjusted Patell (Adj. Patell) and Kolari and Pynnonen (KP) methods.

	MM(-1,+1)	MM(-1,+5)
Announced=0 (286)	-0,08%	-0,29%
KP	(0.8883)	(0.9947)
AdjPatell	(0.9258)	(0.9947)
Announced=1 (115)	-1,68%	-4,85%
KP	(0.3771)	(0.0180)**
AdjPatell	(0.4708)	(0.1632)

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APPENDIX A

A.1 Variable Definitions

Deal Characteristics

All Cash: Dummy variable taking a value of 1 if financed entirely with cash and 0 otherwise.
All Stock: Dummy variable taking a value of 1 if financed entirely with stock and 0 otherwise.
Asset Relatedness: Dummy variable taking a value of 1 if the acquirer and target firms operate in the same industry according to the two-digit Standard Industrial Classification code and 0 otherwise.
Bid Premium: The natural logarithm of offer price over the target's share price, measured four weeks before the deal announcement.
Challenged Deal: Indicator variable taking a value of 1 if the deal is challenged by a third party and 0 otherwise.
Completion Duration: The number of days between deal announcement and completion.
Friendly Deal: Dummy variable taking a value of 1 if the deal attitude is friendly and 0 otherwise.
Horizontal Deal: Dummy variable taking a value of 1 if the acquirer and the target firm are operating in the same sector based on their Fama-French 49 industry classifications and 0 otherwise.
Percent Owned After: The percent of target firm shares held by the acquirer after the transaction.
Tender Offer: Dummy variable taking a value of 1 for tender offer acquisitions and 0 otherwise.
Toehold: The percentage of shares in the target company that are already held by the acquiring firm at the announcement date of the merger.

Firm Characteristics

All firm level characteristics are measured as of the fiscal year-end before the merger announcement, and winsorized at the 1% and 99% levels.

Asset Tangibility: Property, Plant and Equipment expenses divided by the book value of total assets. Compustat Formula is as follows:

$$Asset\ Tangibility = \frac{PPENT}{AT}$$

Cash: Cash and equivalents over the book value of total assets. Compustat Formula is as follows:

$$Cash = \frac{CHE}{AT}$$

HHI (Herfindahl-Hirschman Index): Sum of the squares of the market shares of firms in a two-digit SIC industry, where market share is defined as a firm's sales to the sum of sales within the same industry.

Market Equity: Market value of equity. Compustat Formula is as follows:

$$Market\ Equity = CSHO \times PRCC_F$$

Market Leverage: Market Leverage. Compustat Formula is as follows:

$$Market\ Leverage = \frac{DLTT + DLC}{DLTT + DLC + ME - PSTKL + TXDITC}$$

Market-to-Book (MTB): Market to Book Equity. Compustat Formula is as follows:

$$MTB = \frac{ME}{SEQ}$$

ROA: EBITDA divided by the book value of total assets. Compustat Formula is as follows:

$$ROA = \frac{EBITDA}{AT}$$

R&D Intensity: Research and Development expenses divided by the book value of total assets. Compustat Formula is as follows:

$$R\&D\ Intensity = \frac{XRD}{AT}$$

Size: Logarithm of the book value of total assets. Compustat Formula is as follows:

$$Size = log(AT)$$

Tobin's Q: Market value of assets divided by the book value of assets. Compustat Formula is as follows:

$$Tobin's\ Q = \frac{ME + AT - SEQ}{AT}$$

A.2 Univariate and Multivariate Analysis of Patent Application Rate

Table A.1 Patent Application Rates Around the AIA

Illustrated table summarizes the regression output analyzing the impact of the America Invents Act (AIA) on the patent application rate. The target variables in columns (1) to (5) represent the *Patent Application Rate*, calculated as the fraction of public firms within a given year filing at least one patent application divided by the total number of public firms available in the market. The variables of interest, "*Post-AIA (implementation)*" and "*Post-AIA (enactment)*," take a value of 1 if the year falls after 2013 and 2011, respectively, marking the implementation and enactment dates of the AIA. Data for control variables, including *Change in GDP*, *Trade Openness*, and *Change in Domestic Credit*, come from the World Bank dataset. We employ robust standard errors adjusted for heteroscedasticity. t-statistics are presented in parentheses below the reported coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Patent Application Rate (1)	*Patent Application Rate* (2)	*Patent Application Rate* (3)	*Patent Application Rate* (4)	*Patent Application Rate* (5)
Post-AIA (implementation)	-0.025**	-0.016***	-0.017***	-0.017**	
	(-2.710)	(-6.473)	(-5.523)	(-3.820)	
Post-AIA (enactment)					-0.014*
					(-2.759)
lag Patent Application Rate		0.927***	0.932***	0.875**	0.860
		(7.151)	(6.417)	(4.090)	(1.427)
Change in GDP			0.077	0.044	-0.057
			(1.019)	(0.266)	(-0.307)
Trade Openness				0.001	0.003
				(0.406)	(1.094)
Change in Domestic Credit				0.052	0.095
				(0.797)	(1.197)
Constant	0.242***	0.019	0.017	0.006	-0.060
	(173.9)	(0.593)	(0.490)	(0.156)	(-0.718)
Observations	10	10	10	10	10
R^2	0.479	0.948	0.952	0.961	0.829

APPENDIX B

B.1 Historical Legislative Events in the US Patent System

Table B.1 Key Legislative Events and the Aim of the House

This table summarizes the major legislative events that have shaped the development of the US patent system, from its early foundations in 1953 to the present day.

Event	Year	Intention
Patent Act of 1953	1953	The Patent Act of 1953 represented a major overhaul of the US patent system, aiming to codify and modernize the existing laws. It established a comprehensive framework for patent protection, defining different types of patents (utility, design, and plant patents), outlining the requirements for patentability, and clarifying the process for obtaining and enforcing patents. The Act's intention was to create a more consistent and predictable system that would encourage innovation by providing clear rules for inventors and a reliable framework for protecting their inventions.
Bayh-Dole	1980	This legislation granted universities, non-profit organizations, and small businesses the right to ownership and commercialization of their inventions derived from federally funded research. Following the enactment of the Act, university patenting activity demonstrates a significant increase, potentially promoting technology transfer from academia to industry (Rafferty, 2008).
CAFC	1953	The establishment of the CAFC intend to provide greater consistency and predictability to patent law interpretations, foster a more stable environment for patent holders and innovators. This court's specialized expertise aims to improve the reliability of patent rights enforcement and encourage investment in research and development.
TRIPS	1994	The adoption of the TRIPS agreement required the U.S. to adopt to international standards for IP protection, which aim to increase the global competitiveness of U.S. patents. It aims to ensure that IP laws were in line with global norms, enhance the trust of foreign entities in the U.S. patent system and facilitate smoother international trade and collaboration.

Event	Year	Intention
AIPA	1999	The American Inventors Protection Act (AIPA) of 1999 altered the way patent applications are handled in the US. Prior to AIPA, the intricate details of an invention remained confidential until a patent was granted. Rejected applications or those withdrawn were never publicly disclosed. AIPA mandated the publication of all US patent applications 18 months after the earliest filing date, aligning the US with the international standard of earlier disclosure. This shift aimed to accelerate innovation by fostering greater transparency and public access to emerging technologies.
AIA	2011	The enactment of the AIA significantly reformed the U.S. patent system by shifting to a "first to file" system, which intend to streamline the patent application process and harmonized U.S. practices with international norms. This change aim to reduce patent disputes, expedite patent process, and promote a more efficient and globally competitive market for U.S. innovators.

APPENDIX C

Table C.1 Potential Effects of Independent Variables on Cumulative Abnormal Returns

Explanatory	**Potential Effects on CARs**
warrant ratio	The Securities and Exchange Commission's (SEC) guidance issued on April 12th focused on the accounting treatment of warrants. This has the potential to disproportionately impact SPACs with larger warrant structures, leading to two potential scenarios. On the one hand, the new accounting treatment could be viewed as a stricter regulatory burden, negatively affecting SPACs with a significant number of warrants. On the other hand, if the regulation is interpreted as a measure to enhance governance and protect investors in a potentially volatile market, SPACs with high warrant levels could benefit from the increased transparency and legitimacy associated with adhering to stricter accounting standards.
SPAC Proceeds	The impact of changing market conditions on SPACs might differ based on size. Smaller SPACs, while potentially more susceptible to risk due to their limited resources, may also possess greater agility to adapt quickly. Conversely, larger SPACs, although potentially burdened by slower and costlier adjustments, might benefit from a larger resource pool and a higher capacity to absorb adverse conditions.
months until completion	SPACs nearing their deal deadlines might face increased pressure to identify suitable targets. The SEC's intervention could further complicate their search by introducing regulatory uncertainty into the process. In contrast, SPACs with more time until their deadlines may be less immediately impacted by the deal pressure. However, they could face a future landscape characterized by stricter regulations or potentially less favorable market conditions.
industry-constrained	Stating a targeted acquisition strategy by focusing on a specific industry sector can be a double-edged sword for SPACs. While it may appeal to investors seeking clarity and reduced risk, it could also limit the SPAC's ability to adapt to evolving market dynamics.

Explanatory Variables	Potential Effects on CARs
non-institutional	SPACs with sponsors who hold significant ownership stakes may benefit from more focused attention and guidance. However, such concentrated ownership structures can also limit the sponsor's ability to adapt to changing market conditions. Institutional investors, with their broader networks and financial resources, may offer greater flexibility in navigating challenging environments.