DEPARTMENT
OF ECONOMICS

Essays on Corporate Policies and Lobbying

Nihan Nur Akhan

Thesis submitted for assessment with a view to
obtaining the degree of Doctor of Economics
of the European University Institute

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European University Institute
Department of Economics

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I, Nihan Nur Akhan, certify that I am the author of the work *Essays on Corporate Policies and Lobbying* I have presented for examination for the Ph.D. at the European University Institute. I also certify that this is solely my own original work, other than where I have clearly indicated, in this declaration and in the thesis, that it is the work of others.

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I confirm that chapter 3 was jointly co-authored with Clémence Faivre, Péter Harasztosi, Désirée Rückert, Christoph Weiss and I contributed 50% of the work.

Nihan N. Akhan
05.07.2023

Abstract

This thesis is composed of three essays that examine corporate policies and lobbying behavior.

In the first chapter, **State Level Anti-Patent Trolling Laws and Cash Holding**, I investigate the impact of state level anti-patent trolling laws in the US on firms' cash and debt policies. I claim that anti-patent trolling laws affect corporate policies through two opposing channels: decreasing probability of being a potential target and decreasing uncertainty. I observe that anti-patent trolling laws led to an increase in cash holdings and a decrease in leverage. In line with the targeting strategy of PAEs, I show that the increase in cash holdings and decrease in leverage are mainly driven by innovative firms. I also investigate the interplay between financial constraints and state laws. Results also suggest that the effects on cash and debt are more pronounced for financially constrained firms. Finally, I observe a positive correlation between firms' investment in intangible capital and the introduction of state laws.

The second chapter, **Patent Ownership, Trade and Lobbying**, examines the participation of firms in lobbying on intellectual property rights when they are exposed to trade shocks. Utilizing the data of publicly listed firms and firm level federal lobbying reports in the US, I show that patent-owner firms dominate trade lobbying. Then, I establish a causal link between import penetration from China and lobbying on intellectual property rights using the identification strategy of Autor et al. (2013). As a response to the import penetration from China, I observe that firms increase their lobbying on intellectual property both at the extensive and intensive margin. Results also suggest heterogeneous impact on lobbying. Considering existing results on this subject, this paper provides a striking conclusion: Firms facing competition from China prefer lobbying to investing in innovation.

In the third chapter, **Technological Innovation, Digital Adoption and Firm Performance**, written jointly with Economists from the European Investment Bank, we investigate the impact of digital technology adoption on various firm outcomes. Utilizing the Investment Survey of the European Investment Bank (EIBIS), we first show that the large and productive firms adopt digital technologies. Then, we develop instruments that combine input-output linkages between country-industry groups and sector-specific digital patent stocks to examine the impact of adopting digital technologies on firms' outcome. Results suggest that the digital technology adoption leads to a substantial increase in productivity and wages. Additionally, digital technology adoption positively affects firms' training decisions and management practices as well as their investment in innovation.

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I extend my deepest gratitude to all the participants and organizations who generously contributed their time, knowledge, and resources to this study. Without their involvement, this research would not have been possible, and their contributions have immensely enriched the findings of my thesis.

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Nihan N. Akhan
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Istanbul

Contents

Chapter 1

State Level Anti-Patent Trolling Laws and Cash Holding

Abstract This paper investigates the impact of state level anti-patent trolling laws in the US on firms' cash and debt policies. I find that anti-patent trolling laws led to an increase in cash holdings and a decrease in leverage. Anti-patent trolling laws affect corporate policies through two opposing channels: decreasing probability of being a potential target and decreasing uncertainty. Results suggest that the effect of decreasing possibility of being a target dominates the effect of decreasing uncertainty. I show that the impact of state laws is driven by group of firms that are more likely to be targets of patent assertion entities. Accordingly, I find that the increase in cash holdings and decrease in leverage are mainly driven by innovative firms. Additionally, investigating the interplay between financial constraints and state laws, the results also suggest that the effects on cash and debt are more pronounced for financially constrained firms. Finally, I observe a positive correlation between firms' investment in intangible capital and the introduction of state laws.

1.1 Introduction

The purpose of this paper is to study empirically how anti-patent trolling laws at the state level shape firms' corporate cash and debt policies. By utilizing publicly listed firms in the US, I provide evidence from a quasi-natural experiment created by the staggered introduction of state-level anti-patent trolling laws. I argue that, after the law, the decreasing probability of being a target of PAEs leads firms to increase cash holdings. To shed light on the mechanism, I examine the effect of state laws on firms with various levels of innovation. I find that the increase in cash holdings and decrease in leverage are mainly driven by innovative firms. I also observe a positive correlation between firms' investment in intangible capital and the introduction of state laws.

Roles and activities of Patent Assertion Entities (PAEs) draw particular attention in the US innovation system due to large costs associated with PAEs' activities and rise in patent litigation mostly attributed to them (e.g., Cohen et al., 2019; Feng and Jaravel, 2020 ; Lemley and Feldman, 2016; Miller, 2018). PAEs are a type of company that purchases patents from third parties with the intention of extracting money through licensing contracts, litigation, or both. They are not involved in operations like producing, manufacturing, or selling products (Federal Trade Commission, 2016).[1]According to Miller (2018), unlike the early 2000s, non-practicing entities (NPEs) and patent assertion entities (PAEs) now play a significant role in patent lawsuits.[2] While the rise is observed in litigation cases, the total impact of PAEs can not be limited to litigation since there are different costs (e.g., legal fees and settlement costs) linked to PAEs' activities (Morton and Shapiro, 2013). Based on survey data, direct expenses of NPE patent assertions were estimated as $29 billion by Bessen and Meurer (2013). Despite the fact that these notorious assertions about PAEs call for policymakers to limit their harmful activities, there is no successfully implemented federal legislation in the US.[3] Some states took steps and passed anti-patent trolling laws to eliminate bad faith assertions of patent infringement that might impede local businesses' potential to grow.

State laws which contain some factors to determine whether the infringement claims are done in bad faith or not, are designed to protect the targeted companies by preventing harmful activities of PAEs.[4] Examining how these laws interact with the liquidity decisions of firms allows us both to gain a deeper understanding of the factors affecting corporate liquidity decisions and assess the effectiveness of the state laws. As outlined in literature, cash holding is affected by different motives such as the transaction and precautionary motives, since it allows firms to handle adverse shocks when their access to the capital markets is expensive.[5] In this paper, I claim that the introduction of state laws can have two main

[1]PAEs are also known as non-practicing entities (NPEs), patent monetization entities, or patent trolls. Although every patent assertion entity is a non-practicing entity, not every non-practicing entity (NPE) is a PAE. For example, universities and technology development firms can be NPEs, but they can not be considered as PAEs. However, NPE and PAE can be used interchangeably in literature. In this project, I use patent assertion entity and patent troll interchangeably.

[2]For more details see Miller (2018).

[3]There are some bills considered in the congress but failed to become a law, e.g., the Patent Transparency and Improvements Act (S. 1720), the the Innovation Act (H.R. 3309), the Stopping the Offensive Use of Patents (STOP) Act (H.R. 2766), the Transparency in Assertion of Patents Act (S. 2049), and the Demand Letter Transparency Act (H.R. 1896).

[4]Although the content of the state laws might slightly differ from one state to another, all of them include various factors to detect frivolous infringement claims. Some state laws such as the one enacted by the Alabama legislature also give the right to the targeted party to assert a cause of action and the court may award these part(ies) with the court costs, fees and damages.

[5]See e.g., Favara et al., 2021; Falato et al., 2022; Acharya et al., 2012; Bates et al., 2009; Bates et al., 2018;

opposing effects on firms' corporate policies. On one hand, as empirical evidence suggests, PAEs target firms which are abundant in cash.[6] Accordingly, in the presence of PAEs, firms might have relatively less incentive to hold cash to avoid being a potential target. On the other hand, uncertainty derived from PAEs' activities creates more incentive to hold cash due to precautionary saving channel. For a given cash holding level, by decreasing the probability of being targeted, state laws affect firms' corporate policies through two contrasting channels. After the state law, if the decrease in cash holdings from the uncertainty channel is dominated by the increase in the cash holdings from the probability of being targeted channel, we expect to observe an overall increase in cash holdings. Accordingly, the total effect of the anti-patent trolling state laws would be determined by these two effects. By eliminating alternative motives for cash holding, I show that the probability of being targeted by PAEs dominates firms' corporate policies.[7]

My empirical strategy exploits the fact that state-laws were introduced in various states at different times to investigate their impact on corporate policies. Specifically, I study how changes in the uncertainty and probability of being targeted (for a given cash holding) driven by anti-patent trolling laws affect corporate policies in a difference-in-differences setting. The primary identification assumption underlying this approach is that the timing of the introduction of the state laws is unrelated to other factors driving firms' corporate policies. Indeed, the results suggest that the adoption of state law is uncorrelated with baseline variables. To further alleviate this concern, I perform a series of robustness checks.

I use comprehensive firm level data from Compustat to observe firm level cash holdings and net leverage as well as determinants of these variables. I limit my analysis between 2010-2019.[8] To be able to separate firms into innovative and non-innovative categories, I follow two different strategies. First I construct the R&D stock of firms as in Falato et al. (2022). Also, I use firm level patent data from Arora et al. (2021). This data provides yearly patent data and patent stocks of Compustat firms until 2015. I use this data to separate firms into patent owners and non-patent owners. I also calculate various financial constraint measures and intangible capital of firms following Falato et al. (2022) and Favara et al. (2021).

I find that, after the passage of the laws, the firms experienced an almost a 6% increase in their cash holdings and more than a 80% decrease in their net leverage.[9] I complement my results by using patent and R&D expenditures data. I show that the increase (de-

Opler et al., 1999.

[6]See e.g., Cohen et al. (2019).

[7]I examine the alternative motivations for cash holdings in Section 1.6 in detail.

[8]Anti-patent trolling state laws were introduced in various years between 2013 and 2017.

[9]This number is equal to almost a 8% decrease in leverage once the leverage is used as an outcome variable instead of net leverage.

crease) in cash holdings (leverage) is mostly driven by innovative firms. This result is in line with the targeting strategies of PAEs.[10] Results suggest that, after the passage of the state laws, the channel of being a potential target of PAEs dominates the precautionary saving motive of cash holdings. Additionally, in order to understand the role of the interplay between uncertainty and financial frictions, I investigate differences in responses of firms with varying levels of financial frictions. I observe that the effect of state law on cash holding and leverage is more pronounced when sample is restricted to a relatively more financially constrained firms. Finally, in alignment with the reduction in uncertainty and the probability of being targeted by PAEs, I observe a positive correlation between firms' investments in innovation and the implementation of state laws.

I perform a series of robustness checks to assess the validity of my main results. Indeed, I consider alternative explanations for the observed changes in corporate policies and eliminate them with additional analyses. For example, I replicate the baseline analysis using alternative controls and restricted samples. In addition to testing the common trend hypothesis with event study design, I also use an entropy balancing method to match treatment and control observations. Moreover, to address concerns about biases in two-way fixed effects models caused by heterogeneous treatment effects over time (see e.g., Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021; De Chaisemartin and d'Haultfoeuille, 2020), I revisit the event study approach using the imputation estimator proposed by Borusyak et al. (2022). My results hold under these additional robustness checks.

This paper makes several contributions to the literature. First, this paper contributes to the growing literature related to non-practicing entities, and/or patent assertion entities.[11] Many papers discuss the roles and activities of PAEs in the patent system. Using data related to litigation, Cotropia et al. (2014) and Schwartz and Kesan (2013) provide detailed information on the roles of NPEs/PAEs. More recently, Abrams et al. (2019) links the overall impact of NPEs to the patent infringements that come from non-innovating producers. In addition, Feng and Jaravel (2020) show that the patent examiners have an substantial impact on patent outcomes. They also claim that PAEs impact litigation extensively by preferentially collecting patents granted by experts that ask for fewer changes to patent applications. Chien (2021), Cohen et al. (2019) and Bessen and Meurer (2013) claim that PAEs activities are harmful, especially for small-medium-sized firms and start-ups which have limited ability to defend themselves. There are papers examining the impact of PAEs on firm outcomes.[12] A recent paper by Appel et al. (2019) uses state level anti-patent trolling

[10]See Chien (2021), Cohen et al. (2019)Bessen and Meurer (2013).

[11]Since most of the papers use NPEs and PAEs interchangeably, I use this terminology to summarize literature.

[12]See e.g., Cohen et al., 2019; Smeets, 2015; Tucker, 2014; Kiebzak et al., 2016.

laws and found that state level laws lead to an increase in high-tech employment of start-ups driven by the IT industry. I contribute to this literature in two ways. First, I focus on the impact of the state level intervention on corporate policies. Second, I offer an alternative perspective to this topic by demonstrating the response of the larger, publicly listed corporations that have the abilities and resources to deal with PAEs.[13].

My analysis also contributes to the vast literature on corporate cash holdings. According to the literature investigating the relationship between corporate decisions and uncertain environments, precautionary savings is considered as one of the most important motivations for corporate cash holdings since cash holdings can be used as a cushion for future funding needs under uncertainty.[14] Numerous papers investigate the relationship between uncertainty, financial frictions and cash holdings.[15] A recent paper by Falato et al. (2022) adds to corporate cash holding literature by emphasising the importance of the use of intangible capital. They claim that cash holding patterns of firms are closely linked to intangible capital levels. Another recent paper by Favara et al. (2021) investigates the impact of staggered introduction of anti-re-characterization laws in US states on firms' cash and debt policies. While many papers aim to explain the link between corporate decisions and uncertainty, my findings add another layer to this topic by providing alternative channels and novel evidence to a longstanding debate about anti-patent trolling laws. This study can be seen as an initial step to understand the consequences of the interventions influencing firms' debt decisions and propensity to save within the context of patent related laws.

The remainder of the paper is organized as follows. Section 1.2 summarizes the institutional background of the topic. Section 1.3 provides a conceptual framework. Section 1.4 discusses data and the methodology. Section 1.5 presents the baseline results and various robustness checks. Section 1.6 argues alternative explanations for cash holdings. Section 1.7 concludes.

1.2 Institutional Background

The roles of PAEs are widely discussed. On the one hand, it is claimed that these entities are useful for monetization of inventions and acting like intermediaries by fostering in-

[13]The results provided in this paper do not contrast with the possibility of state laws being effective in eliminating the harmful activities of PAEs and being beneficial particularly for small firms with limited ability to defend themselves. Due to data unavailability, I cannot add to this discussion.

[14]See e.g., Opler et al. (1999); Bates et al. (2009); McLean (2011)

[15]See e.g., Acharya et al. (2012); Opler et al. (1999); Bates et al. (2009);Denis and Sibilkov (2010) ; Lins et al. (2010); McLean (2011); Almeida et al. (2004).

centives to innovate through improving the matching between patent holders and patent buyers (e.g., Abrams et al., 2019; Cotropia et al., 2014) On the other hand, it is discussed that the PAEs are involved in frivolous claims to extract money from the targeted firms. It is claimed that by obtaining patents with ambiguous boundaries, they send threat letters[16] and request licensing payments from inventive enterprises, regardless of whether the asserted patent is legitimate or infringed.[17] In addition to demanding money via sending letters, PAEs are involved in patent infringement litigation. An important feature of their litigation activity is the forum shopping behavior since patent infringement cases can be filed in any state regardless of the location of the parties being sued.[18] Although this behaviour was limited due to the US Supreme Court decision, TC Heartland LLC v. Kraft Foods Group Brands LLC, 581 U.S. (2017), many patent infringement lawsuits brought by PAEs before this date were concentrated in the Eastern District Court of Texas, due to favorable conditions offered to the patent holders (Leychkis, 2007 ; Kiebzak et al., 2016).[19]

In order to understand the consequences of PAEs activities, it is crucial to comprehend their targeting strategies. Even though PAEs might target different types of firms, there are particular patterns in their targeting strategies. According to Federal Trade Commission (2016) and Allison et al. (2019), a significant part of infringement claims are related to software patents that have fuzzy boundaries. Furthermore, United States Government Accountability Office (2013) investigated patent infringement lawsuits from 2000 to 2010. Report suggest that NPEs are responsible for the non-negligible part of the lawsuits and most of them include software-related patents. Federal Trade Commission (2016) also investigated industries of subject firms. They found that the significant share of subject firms are from two main industry categories: "Manufacturing" and "Information". In more detailed analysis, they also found that a large proportion of subject firms belong to the high-tech sub-sectors of manufacturing and information sectors such as Computer Electronic Product Manufacturing and Telecommunications. Chien (2021) also claimed that the important part of the demands by PAEs include software or high-tech patents. Similarly, Allison et al. (2019) suggested that activities of PAEs greatly affect the computer and electronics industries and communications industries.

Recent studies are mostly in favor of the claim that the PAEs are involved in abusive

[16]One example of the threat letter by a patent assertion entity is shown in the Figure A.1.1 in the Appendix . This letter is taken from `https://trollingeffects.org/letters`.

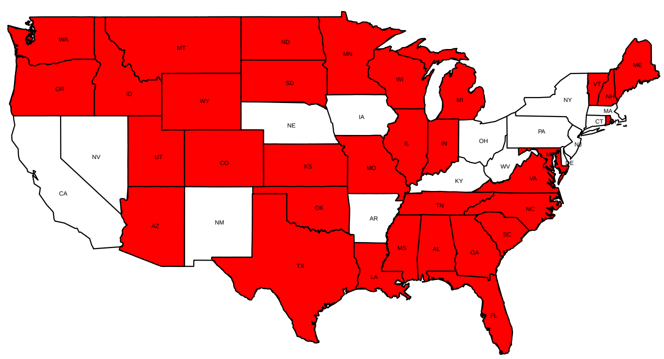
[17]See e.g., Allison et al. (2019); Cohen et al. (2019) ; Chien (2021) ; Feng and Jaravel (2020) ; Miller (2018).

[18]See Leychkis (2007).

[19]In 2017, Supreme Court ruled, that the patent infringement cases must be heard in the states where the defendant is incorporated and/or has an established business location. For more detail see *TC Heartland LLC v. Kraft Foods Group Brands LLC*, 581 U.S. (2017).

activities.[20] It is claimed that PAEs target firms that have limited ability to defend themselves and they are detrimental for the innovation and venture capital investments.[21] Due to importance of the issue, many bills are proposed in Congress to restrict the abusive behaviours of PAEs. However, none of the proposed bills became law.[22] As stated by Boldrin and Levine (2013), many actors influence the political economy of patent protection. One of the controversial patent bills regarding patent assertion entities is proposed by U.S. Senator Patrick Leahy (Patent Transparency and Improvements Act, 2013). Due to disagreements between groups, the patent reform bill could not reach any conclusion. Supporters of this bill such as Coalition for Patent Fairness and the Internet Association, which includes firms like Google and Facebook, stated their opinion regarding this subject.[23] On the other hand, Intellectual Ventures, a well-known large PAE, was involved in lobbying on this particular bill and many other related bills.[24]

Figure 1.1: States with Anti-troll Laws



The lack of steps to pass federal law regarding the subject urged some states to enact their own legislation. In 2013, Vermont was the first state to pass an anti-patent trolling law. Several other states enacted similar legislation in the following years. The signing

[20]e.g., Bessen and Meurer (2013); Chien (2021) ; Cohen et al. (2019); Feng and Jaravel (2020)).

[21]e.g., Bessen and Meurer (2013); Chien (2021) ; Cohen et al. (2019); Kiebzak et al. (2016).

[22]The last patent reform is signed by former President Obama in 2011. It was called the America Invents Act (AIA) and it was mostly related to replacing the 'first to invent' patent system with a 'first inventor to file' system. A couple of failed bills include The Innovation Act (2013); The Transparency in Assertion of Patents Act (2014); The Demand Letter Transparency Act (2015). For the many other bills proposed, see e.g., Cohen et al. (2019)

[23]See Bartz (2014) and Servick (2014).

[24]Author's own investigation from the federal level lobbying reports available via https://www.lobbyview.org.

years of states can be found in the Table A.1.1 in Appendix A.1. States passed anti-patent trolling legislation is marked as red in the Figure 1.1 above.[25]

1.3 Conceptual Framework

In this section, I briefly discuss the mechanism behind the change in the cash holdings and debt levels with a simple conceptual model. In line with the Han and Qiu (2007), I consider two period-production model in which firms maximize the expected lifetime sum of all dividends (d). Production takes place in second period where production functions using capital levels k_1 and k_2: $g(k_1)$ and $\pi(k_2)$. Production functions follows the simplest form with a parameter $\alpha > 0$ such that $g(k_1) = k_1^\alpha$ and $\pi(k_2) = k_2^\alpha$ and satisfy the following assumptions: $\pi_k(k) > 0$, $\pi_{kk}(k) < 0$, $\pi_{kkk}(k) > 0$, $g_k(k) > 0$, $g_{kk}(k) < 0$, and $g_{kkk}(k) > 0$. I also assume that the firm start period 0 with initial amount of cash, denoted by c_0. Starting the period with initial amount of cash, c_0, the dividend paid by firm in period 0 is a function of borrowing (b), capital (k) and cash holding (c) choices in these period, $d_0 = c_0 + b_1 - k_1 - c_1$. For simplicity, I assume that there is no interest payment on the repayment of the debt and no cost on issuing debt. In period 0, the borrowing constraint is $b_1 \leq \theta k_1$. The liquidation value of assets that can be captured by creditors is given by θ, where $\theta \in (0, 1)$. While the dividend paid in first period is as follows: $d_1 = c_1(1+r)+b_2-k_2-p(c_1)F$ where b_2 and k_2 denotes the borrowing and capital levels. In this period, there is a probability of being targeted by PAE, p(c_1)=c_1^γ. If firm is targeted by PAE, there is a fixed cost of being targeted denoted by F. The borrowing constraint is $b_2 \leq \theta k_2$. Finally, dividend paid by firm in period 2 is as follows: $d_2 = g(k_1) + \pi(k_2) - b_1 - b_2$. In period 2, the production takes place and all of the debts are paid.

Firm's objective is to maximize the expected lifetime sum of all discounted dividends where discount factor is normalized to 1 for simplicity. Firm chooses k_1, k_2, b_1, b_2 and c_1 subject to borrowing constraints and non-negativity constraints for the dividends, $d_0 \geq 0$, $d_1 \geq 0$ and $d_2 \geq 0$.[26] For the constrained firm, forgoing a dividend payment in period 0 and period 1 is a zero NPV and borrowing an additional dollar is also a zero NPV project. Therefore, it is optimal for the constrained firm not to pay any dividends in period 0 and period 1 and to exhaust its borrowing capacity. Using these conditions, capital levels can be formulated as a function of initial cash holding, c_1 and parameters. Using these conditions,

[25] Although some papers such as Appel et al. (2019) suggest that Connecticut passed anti-patent trolling law in 2017, Institute of Politics Technology Policy Group (2019) claims that there is no anti-patent trolling law in Connecticut. To avoid confusion I drop Connecticut from my sample. My results are robust to including Connecticut as a state with anti-patent trolling law.

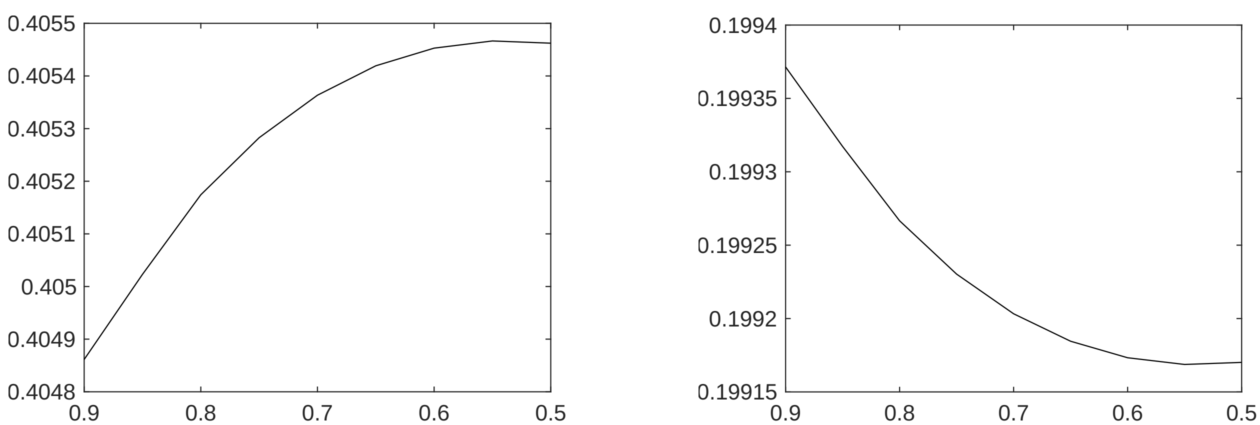
[26] Details of the firm problem can be found in the Appendix A.2.

the optimal cash holdings c_1^* satisfy the following first-order condition:

$$(1 + r - p'(c_1^*)F)(\pi'(\frac{(1+r)c_1^* - p(c_1^*)F}{1-\theta}) - \theta) = g'(\frac{c_0 - c_1^*}{1-\theta}) - \theta$$

I consider state law is an event decreasing the probability of being targeted for a given cash holding (e.g., decrease in the γ). For a given level of cash holding, as γ decreases, on one hand, marginal return from holding cash holding $(1 + r - p'(c_1^*)F)$ increases. On the other hand, marginal return from holding tangible capital $\pi'(\frac{(1+r)c_1^* - p(c_1^*)F}{1-\theta})$ is decreasing.[27] The overall effect on the optimal cash holding is determined by the relative increase/decrease in these terms. To be able to show closed form solutions and perform comparative statistics, I make simplifying assumptions for the production and probability functions. These analyses can be found in the Appendix A.2.

Figure 1.2: Numerical Analysis



(a) Cash/Asset

(b) Debt/Asset

Note. Numerical analysis. Panel (a) plots the evolution of cash to asset ratio and panel (b) plots debt to asset ratio for the different levels of γ, parameter in the probability function. The x-axis is reversed. γ is defined as a vector over a certain range from 0.9 to 0.5. The decreasing γ reflects the introduction of the state law.

I numerically solve the model by using parameters from the literature. For the initial cash holding, I use the average cash holding in my sample. I calculate the cost associated with the PAEs using the data from Bessen and Meurer (2013). First, I use the average aggregate cost of PAEs per firm. Then, I calculate the share of cost associated with the PAEs in firms' revenue from Bessen and Meurer (2013) and normalized this value with the average revenue in my sample.[28] I also use other parameters from the literature. I select the range

[27] Note that the conceptual model do not explicitly model uncertainty but change in the probability affects the future income.

[28] In detail, I utilize the numbers in Table 1 and Table 4 from Bessen and Meurer (2013). First, I utilize the average of total cost and constructed a cost per firm. Then, using the mean revenue levels from Table 1 in

of γ parameter following the results of Cohen et al. (2019).[29] θ and α values are gathered from Nikolov and Steri (2019) and interest rate from Falato et al. (2022). The simple numerical solutions suggest that as the the probability of being targeted decreases (e.g., as γ decreases), the cash holding increases and leverage decreases.[30] These results can be observed in the Figure 1.2 above.[31]

1.4 Data

This section explains the dataset that is used in this paper. It also provides information on the construction of main variables.

1.4.1 Sample

This study uses all publicly traded US firms from Compustat. I follow simple cleaning procedures to construct the sample. First, I exclude all the firms operating in the financial sector, regulated utilities and the public sector as in Favara et al. (2021) and Falato et al. (2022). I limit my sample to 2010-2019 due to better coverage of the data after the 2000s and to eliminate the financial crisis period. State laws were introduced in different years between 2013-2017.[32] I use the headquarter location of the firms as the operating location. [33] Since Compustat only provides the most recent data on the headquarters, I use the historical headquarter information from Gao et al. (2021). I dropped the firms that changed their headquarters. Similar to Falato et al. (2022), I use firm fixed effects in my analysis

their paper, I calculated the share of cost in revenue for the sample in Bessen and Meurer (2013). Finally, I multiply this value with the mean revenue in my sample to construct artificial cost associated with the PAEs. Note that, I scale the monetary values to solve the model numerically.

[29]Results of Cohen et al. (2019) suggest that the %1 increase in the cash holding increases the probability of being sued by NPE by 0.000565. This number is equal to almost 0.66% increase in probability of being sued by NPE considering the mean probability of being sued by NPE. Given the functional form assumptions in this section, the γ is defined as a vector over a range including 0.66.

[30]Note that as expected the results are sensitive to the parameter selection since the impact of γ on cash holding depends on the levels of F, and other parameters. For the discussion on comparative statistics, refer to the Appendix A.2.

[31]Results show the cash to asset ratio and debt to asset ratio (using c_1 and d_1)

[32]Although Vermont passed the law in 2013, firms operating in Vermont is very limited and eliminated in the cleaning and trimming procedures. Also note that, although some papers such as Appel et al. (2019) suggest that Connecticut passed anti-patent trolling law in 2017, Institute of Politics Technology Policy Group (2019) claims that there is no anti-patent trolling law in Connecticut. To avoid these confusion, I drop Connecticut from my sample. However, the results would not change if I keep Connecticut in my sample as a treated firm. These results are available upon request.

[33]Note that, it is possible that a firm can operate in multiple locations and it is natural to consider that relatively bigger firms operate in many states. However, results focusing on firms' sizes , presented in the 1.5.2, eliminate this concern by showing that the results are mostly driven by the relatively smaller firms. Therefore, this issue becomes less of a problem since smaller firms are less likely to operate in many locations.

and I limit my sample to the firms observed consecutively at least for 3 years.[34] Following Falato et al. (2022) and Favara et al. (2021), I consider cash to asset ratio and cash to net asset ratio as a dependent variables. In addition, I also construct the net leverage ratio as net debt to asset ratio. For all the control variables, I follow the construction explained in Falato et al. (2022). As control variables, I constructed cash flow to asset, acquisitions expenditures to asset, market to book ratio, firm size (assets in 2000 dollars or employment), capital expenditures to assets and dummy variable if firm performs R&D in that year (1 if reports positive R&D expenditure, zero otherwise), dividend paying status (if reports dividend payment) and industry level cash flow volatility. Finally, I trim top 1 and bottom 1 percent of some variables such as cash flow, market to book ratio and cash holdings to eliminate abnormalities.[35]

To contrast the response of innovative firms to less innovative firms, I follow the following steps. First, I constructed R&D stock of each firm. I follow the construction methodology presented in Falato et al. (2022). R&D stock is measured by capitalizing R&D expenditures using the perpetual inventory method with a depreciation rate of 15%. I also set the initial R&D stock to be equal to the first year the R&D expenditures of a firm divided by the depreciation rate. Using these stock values, I separate firms into two groups according to their R&D stock status[36]) before the initial state law. I label firms with positive R&D Stock before the first state laws as innovative while the others are labelled as non-innovative. Second, I merged the data with the patent data provided by Arora et al. (2021).[37] I created this measure by simply assuming that the firms with a positive stock of patents before the introduction of the initial state laws are relatively innovative ones. Using these different firm level innovation measures, I investigated the response of the firms to the introduction of state-laws by separating samples into innovative (patent-owner) and less innovative firms (non-patent owner).

I constructed a firm-year level intangible capital stock following Falato et al. (2022). It consists of R&D stock, organizational capital stock (SG&A stock), and the stock of computerized information. Similar to R&D stock, I calculated the firm level SG&A stock with a depreciation rate of 20%. As in Falato et al. (2022), I weigh the stock of organizational capital by 0.2 in total intangible capital. Finally, I construct the stock of computerized information and software (informational capital). It is calculated as the using industry level

[34]I also limit my sample to 2012-2019 to observe two years before the first state law and two years after last state laws. These results are presented in Table A.6.2. Results are also robust to limiting the sample to firms observed at least one year before and after the state laws. These results are available upon request.

[35]For more detail on the variable construction see Appendix A.3

[36]I separate firms into two groups depending on their R&D Stock (positive or zero).

[37]Unfortunately, the yearly patent variables and patent stocks are only observed until 2015. Therefore, this variable can not be used as a dependent variable.

BEA Fixed Reproducible Tangible Wealth (FRTW) data with a depreciation rate of 31%. After constructing cumulative stocks and normalizing it by the industry total assets, I link these stocks to firm level. To map these stocks to firm level, I calculated tangible capital stock (PPE) for each firm to derive a firm-level stock. I multiply each industry level stock with the firm level tangible capital stock. In Subsection 1.6.1, I investigate the impact of anti-patent trolling law on firms' R&D stock, organizational capital stock, informational capital stock and intangible capital; free of information capital stock (normalized by total assets).[38]

I also constructed standard financial friction measures similar to Falato et al. (2022). By following literature, I created different ex-ante financial friction measures for every firm. I consider the following financial constraint measures: firm size (total assets and sales), the WW-index Whited and Wu (2006), external finance dependence Rajan and Zingales (1998) and asset liquidity by Berger et al. (1996). First I calculate the average of each measure for each firm using the data before the introduction of the state laws. Then depending on the distribution of these average measures, I separate firms into two groups, as financially constrained and financially non-constrained ones, depending on the median value. Table 1.1 presents a summary statistics from the sample. While employment is presented in hundreds, monetary values such as WW-Index and Asset Liquidation Index are in millions of dollars. All monetary values are deflated to 2000 prices using the Consumer Price Index. The sample covers the years between 2010–2019.

[38]Note that, as explored in Section 1.6.1 since state-law has no impact on informational capital stock, I consider intangible capital as the sum of R&D stock and organizational capital stock. When informational stock is added to intangible capital, the results are statistically insignificant while economically non-negligible.

Table 1.1: Descriptive Table

Statistic	N	Mean	St. Dev.	Median	Pctl(25)	Pctl(75)
Cash/Asset	15,103	0.206	0.215	0.129	0.043	0.294
Cash/Net Asset	15,103	0.522	1.234	0.148	0.045	0.416
Net Leverage	15,103	0.039	0.385	0.046	−0.200	0.278
Log(Total Assets)	15,103	19.575	1.973	19.801	18.261	21.055
Log(Sales)	15,103	19.381	2.219	19.722	18.027	21.004
Employment	15,103	7.474	22.038	1.560	0.285	6.300
Acquisitions	15,103	0.023	0.055	0.000	0.000	0.013
CashFlow	15,103	−0.005	0.257	0.066	0.003	0.104
Capital Expenditures	15,103	0.046	0.061	0.029	0.014	0.055
Market to Book Ratio	15,103	2.172	1.588	1.644	1.200	2.516
HHI	15,103	0.357	0.268	0.284	0.147	0.500
R&D (Dummy)	15,103	0.536	0.499	1	0	1
R&D (Stock)	15,103	0.283	0.744	0.030	0.000	0.260
Organizational Capital (Stock)	15,103	0.227	0.268	0.152	0.072	0.283
Informational Capital (Stock)	15,103	0.471	1.083	0.186	0.070	0.393
Dividend Status	15,103	0.347	0.476	0	0	1
External Finance Index	14,981	22.014	482.737	−0.665	−2.635	0.887
WW-Index	12,890	−0.852	1.258	−0.897	−0.967	−0.810
Asset Liquidation Index	14,907	0.226	0.123	0.211	0.132	0.305

Summary statistics. This table reports the summary statistics of the main variables. The sample period spans 2010–2019. Employment is in hundreds. Assets and sales are in logs and in 2000 dollars (using CPI). The R&D (stock) organizational capital (stock), and informational capital (stock) are normalized by total assets.

Other Dataset To be able to show that the baseline variables do not affect states' decision to adopt anti-patent trolling laws, I use additional datasets. For employment, GDP levels and population levels, I utilize the Employment by State Statistics and Regional Economic Accounts of The Bureau of Economic Analysis, respectively. I use the statistics from USPTO for the patent levels. For educational attainments and venture capitals at the state level, I use Science & Engineering State Indicators from the National Science Foundation (NSF). Unemployment rates are taken from Local Area Unemployment Statistics of the U.S. Bureau of Labor Statistics (BLS).

1.4.2 Empirical Strategy

In this subsection, I discuss the empirical strategy. First, I investigate the response of firms' cash and debt to the introduction of anti-patent trolling laws by estimating a difference-in-differences.

$$Y_{i,j,s,t} = \mu_i + \gamma_t + \beta_1 PostEvent_{i,j,s,t} + +\delta \mathbf{X}_{i,t} + \epsilon_{i,j,s,t} \tag{1.1}$$

where $Y_{i,j,s,t}$ is one of the following variables: cash/asset, cash/net assets, net leverage for firm i in industry j in state s at time t and μ_i and γ_t are the firm and year fixed effects. $PostEvent_{i,j,s,t}$ takes value of 1 for firm i operating in sector j in states (HQ) with anti-patent trolling law at time t. Finally, $\mathbf{X}_{i,t}$ denotes for the firm controls such as cash flow, capital expenditure, acquisitions (all normalized by assets), market to book ratio, R&D dummy, log employment, dividend payment dummy and industry cash flow volatility.[39] β_1 main variable of interest and it is expected to have opposite positive sign for the cash holding if the impact of probability of being targeted dominates impact of uncertainty after the laws.

Second, I investigate the impact of state-laws with DifferenceinDifference (DID) event study. Formally, I estimate the following equation:

$$Y_{i,j,s,t} = \mu_i + \gamma_t + \sum_{\tau=-Tmin}^{Tmax} \beta_\tau Treat_{i,j,s,t,\tau} + \delta \mathbf{X}_{i,t} + \epsilon_{i,j,s,t} \tag{1.2}$$

The binary event-time indicator $Treat_{i,j,s,t,\tau}$ takes value one if , τ = t $-$ τ_s, where τ_s is the first time that anti-patent trolling law is available in state s, and zero otherwise. $Tmin$ and $Tmax$ are the lowest and highest number of leads and lags to consider surrounding the treatment period, respectively. To be able to deal with the potential biases that can result from applying a two-way fixed-effect (TWFE) regression estimator on such a staggered setup, I also estimate the equation using the imputation estimator proposed by Borusyak et al. (2022).

1.5 Baseline Results

In this section, I present the baseline results. Table 1.2 presents difference-in-differences estimates of firms' cash and debt decisions to the introduction of anti-patent trolling state laws. The first three columns report the estimates without the control variables. While, the last three columns present the results with the controls. Results suggest that the anti-patent trolling laws are associated with a more than 6% increase in cash holdings while they are linked to more than 80% decrease in net leverage.[40]

Results suggest that, after the state laws, the impact of decreasing probability of being targeted dominates the impact of decreasing uncertainty. In order to establish a causal link,

[39] Although industry cash flow volatility is at the SIC2-year level the notation is manipulated for brevity.

[40] This number is equal to almost a 8% decrease in leverage once the leverage is used as an outcome variable instead of net leverage. Additionally, Instead of considering the cash to asset ratio, I also consider the log of cash to asset ratio, log of cash to net asset ratio as in Bates et al. (2009) and leverage instead of net leverage as alternative outcome variables. These results are available upon request.

Table 1.2: Baseline Results

	Cash/Asset (1)	Cash/N.Asset (2)	N.Leverage (3)	Cash/Asset (4)	Cash/N.Asset (5)	N.Leverage (6)
Variables						
PostEvent	0.0141**	0.1173**	-0.0316**	0.0137***	0.1201**	-0.0339***
	(0.0060)	(0.0547)	(0.0131)	(0.0049)	(0.0515)	(0.0116)
Fixed-effects & Controls						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	Yes	Yes	Yes
Fit statistics						
Observations	15,103	15,103	15,103	15,103	15,103	15,103
R^2	0.86526	0.75219	0.82210	0.87637	0.76045	0.83623
Mean	0.2063	0.5216	0.0386	0.2063	0.5216	0.0386

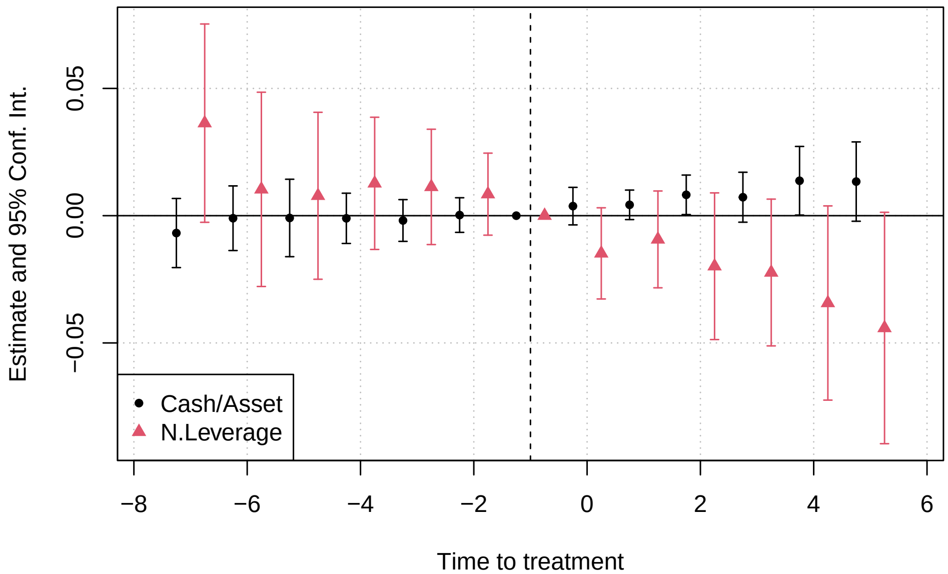
Note. Clustered (State) standard-errors in parentheses. *p<0.1; **p<0.05; ***p<0.01. Firm controls include cash flow, capital expenditure, acquisitions (all normalized by assets), market to book ratio, R&D report dummy, log employment, dividend paying status in any given year and industry cash flow volatility.

I check common trends of treated and control firms before the introduction of state laws. I follow standard event study design to check whether there is a violation of common trend assumption or not. Figure 1.3 presents the results of simply estimating the equation 1.2. Indeed, we observe an increase in estimates of cash holdings and decrease in leverage for the years following the state laws.

In order to alleviate the concerns regarding introducing state laws being endogenous to baseline variables such as employment, GDP and state innovation levels, I simply check whether the introduction of state laws is affected by the baseline variables. All baseline characteristics are from the year 2010. Figure 1.4 presents the results of an estimation at the state level. It shows that none of the baseline standardized variables affect the states' decision to introduce anti-patent trolling state laws. Table A.4.1 in Appendix A.4, presents results with standardized baseline variables using the firm level data.

I examine the potential channel(s) behind the increase in cash holding and decrease in leverage as a response to the introduction of anti-patent trolling state laws. I claim that if being a potential target is alleviated after the state law, we expect that the results are mostly driven by the firms which are potential targets of PAEs. If this channel is legitimate, we should observe the change in the cash holdings (leverage) is driven by mostly innovative firms. I calculate R&D stocks as explained in Section 1.4. Using patent data Arora et al. (2021) and constructed R&D stocks, I classify firms into innovative (patent-owner) and non-innovative (non patent-owner) depending on their R&D and patent stock status before the initial state law. The details of this separation are explained in Section 1.4

Figure 1.3: Event Study: Cash/Assets and N.Leverage



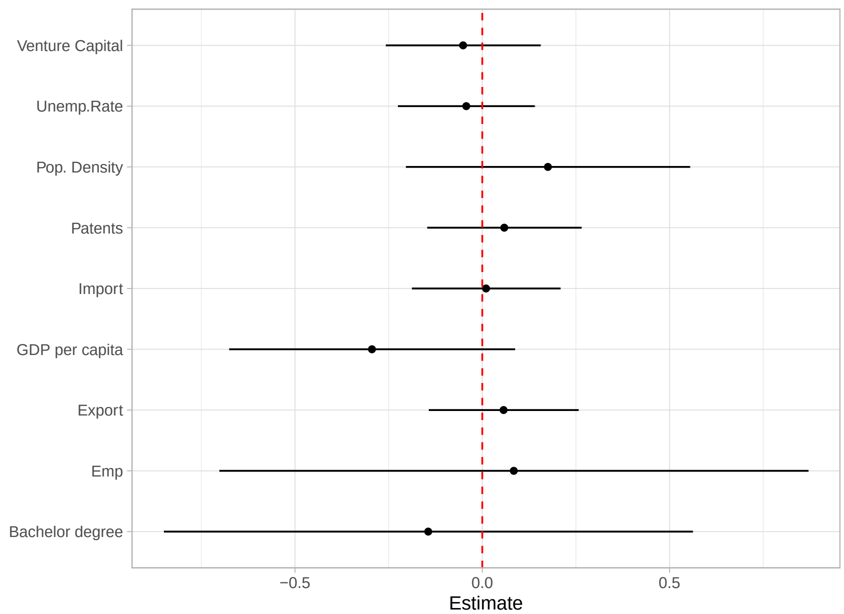
Note. The figure presents the effect of anti-patent trolling laws on firms' cash and net leverage around the years of the anti-patent trolling laws adoption. I estimate the equation 1.2. The intervals around the dots represent 95% confidence intervals. Regressions include firm and year fixed effects and controls. Standard errors are clustered at the state level.

in detail.[41] By simply separating the sample into two groups, I observe that the impact of anti-patent trolling laws is driven by innovative firms. Figure 1.5 presents the results using R&D stock and Figure 1.6 shows results using patent ownership. The regressions corresponding to the presented tables can be found in Table A.4.2 and Table A.4.3 of Appendix A.4. The first three columns show the results for the innovative firms (patent-owner) while the last three columns present estimates for the non-innovative (non patent-owner) firm sample.

As results suggests, the impact of the state laws on cash holdings and leverage is driven by innovative firms, while the impact on non-innovative firms is both economically and statistically insignificant. One may argue that the state laws might affect the R&D decisions of the firms after introduction. To be able to eliminate these concerns, I separate firms into two different groups by looking at the R&D performing status until the introduction of the

[41]Note that I also take into consideration the separation of firms based on the median level of intangible capital before the implementation of state laws. Given that intangible capital include multiple components and many firms have a positive intangible capital, relying solely on the intangible capital status (as in R&D or patent stock) of firms would not be a valid approach for separation. Instead, I separate firms based on the median level.

Figure 1.4: Determinants of the Anti-patent Trolling Law Adoption



Note. This figure plots the estimates from the analysis investigating the relationship between baseline variables and adoption of anti-patent trolling law at the state level. All the baseline characteristics from the year 2010. The unit of observation is state. All baseline characteristics are standardized to have mean zero and standard deviation one to facilitate comparisons. Error bars represent 95% confidence intervals. Table A.4.1 in Appendix A.4, presents results with standardized baseline variables using the firm level data.

initial state law.[42] Additionally, instead of using R&D stocks, I use the patent data provided by Arora et al. (2021). After separating firms into two different groups depending on their patent owner status before the initial state law, I observe similar results.[43]

1.5.1 Robustness

In this section I perform series of robustness checks to assess the credibility of baseline results.

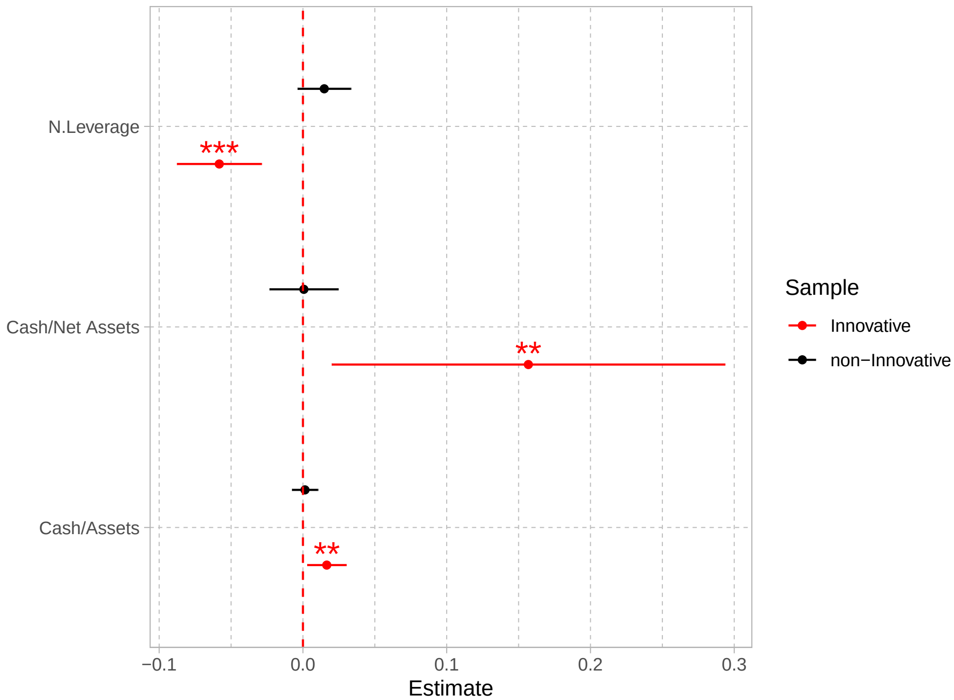
Alternative control variables First, I consider additional state level controls in the regression. I include the state level total sales and R&D expenditure as an additional control variable. Second, instead of using yearly control variables, I also use the lag of the control variables. The results of these estimations are reported in Table 1.3.[44]

[42] I also interacted the R&D stock status and yearly R&D decision with the PostEvent indicator. These results suggest that the innovative firms increase their cash holding more than non-innovative firms. They are presented in the Table A.4.4 in Appendix A.4.

[43] In Appendix A.5 I also provide additional evidence on the probability of being targeted channel.

[44] I also consider log total assets (deflated) instead of log employment to control firm size. Additionally, I consider lag of dependent variables in addition to the lag of other control variables. Results are robust to these specifications. These results can be found in the Table A.6.1 in Appendix A.6. I also consider the lag of total assets in addition to the lag of other control variables. Results are also robust to this specification.

Figure 1.5: Comparing Innovative and non-Innovative Firms



Note. The figure presents the effect of anti-patent trolling laws on firms' cash and leverage by separating sample into two groups (depending on their R&D Stock status before the first state laws. See 1.4 for more details). I estimate the baseline equation 1.1 for each sample. The error bars represent 95% confidence intervals. Regressions include firm and year fixed effects and controls. Standard errors are clustered at the state level.

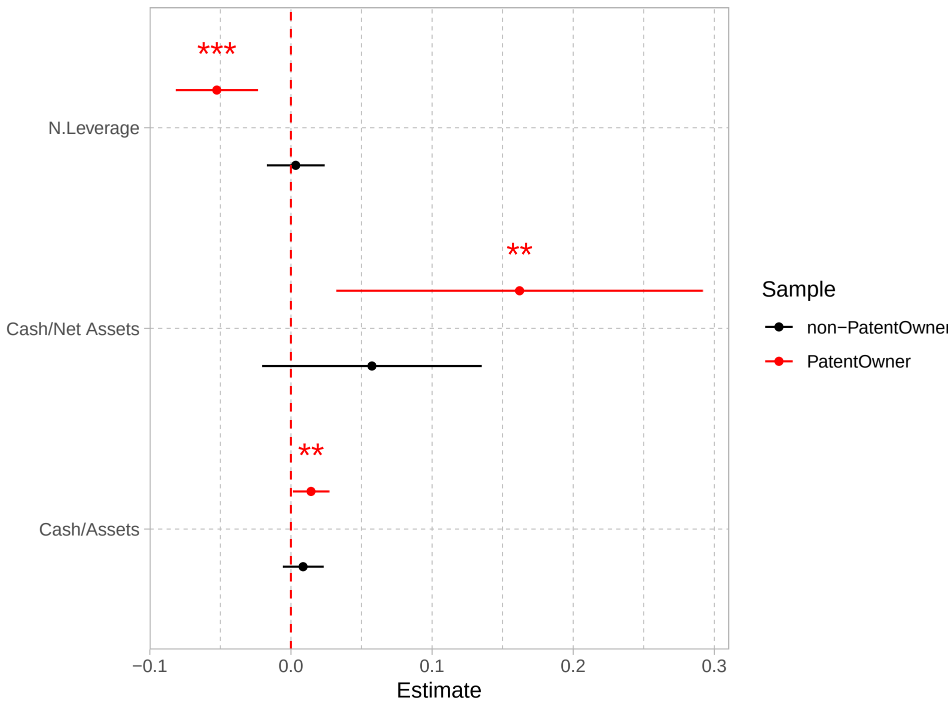
Adjustments to the sample I exclude California from the sample and re-estimate baseline results to alleviate the concerns that big-innovative state driving the results. The impact of anti-patent trolling state laws still have a statistically and economically meaningful impact on the cash and debt decisions after excluding California from the sample. These results are presented in the Table 1.4 below.[45]

Industry Trends In order to control industry trends, I add two digit sector(SIC2)-year fixed effects to the estimation. The first three columns of Table 1.5 present these results. While the first three columns present the results without the controls last three column presents with control variables. Results suggest that the controlling industry trends do not have any impact on the results.

Falsification Test In order to increase the credibility of the results and eliminate the concerns about spurious correlations, I performed a falsification exercise. In particular, I

[45] I also limit my sample to 2012-2019 to observe two years before the first state law and two years after last state laws. Although Vermont passed the law in 2013, firms operating in Vermont is very limited and eliminated in the cleaning and trimming procedures. These results can be found in the Table A.6.2 and results are robust to this sample adjustment.

Figure 1.6: Comparing for Patent Owner Firms vs non-Patent Owners



Note. The figure presents the effect of anti-patent trolling laws on firms' cash and leverage by separating sample into two groups (depending on their Patent ownership status before the first state laws. See 1.4 for more details). I estimate the baseline equation 1.1 for each sample. The error bars represent 95% confidence intervals. Regressions include firm and year fixed effects and controls. Standard errors are clustered at the state level.

falsely assign random anti-patent troll legislation years to the states between 2010-2019. I do not assign any dates to the control states. Using this false random anti-patent trolling law years, I estimate the baseline equation 1.1 by using cash holdings and leverage as dependent variables. Figure A.6.1 in Appendix A.6 shows the distribution of the estimates of 500 repetitions. The estimates from the baseline regressions are presented with a dotted red line. Results suggest that the mean of the estimates from the falsely assumed an-patent trolling laws is close to zero and the baseline coefficient is outside of the support of the distribution. This test alleviates the concerns about spurious correlations.

Excluded treatment cohorts Finally, I exclude each cohort of state laws from the sample and investigate the impact of the state laws.[46] Table A.6.3 in Appendix A.6 presents the results. All of the estimates are statistically and economically significant even after excluding different cohorts from the sample.

Entropy balancing Finally, I estimate the effect of anti-patent trolling laws with an entropy balancing method. I categorize firms into two groups depending on treatment, e.g.,

[46] Although Vermont passed the law in 2013, firms operating in Vermont is very limited and eliminated in the cleaning and trimming procedures.

Table 1.3: Alternative Controls

	State Level Controls			Lag Controls		
	Cash/Asset	Cash/N.Asset	N.Leverage	Cash/Asset	Cash/N.Asset	N.Leverage
	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
PostEvent	0.0133**	0.1153**	-0.0326***	0.0126**	0.0789**	-0.0291***
	(0.0051)	(0.0515)	(0.0117)	(0.0048)	(0.0357)	(0.0102)
Fixed-effects & Controls						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	15,103	15,103	15,103	12,890	12,890	12,890
R^2	0.87635	0.76043	0.83623	0.88227	0.80033	0.84527
Mean	0.2063	0.5216	0.0386	0.2016	0.4848	0.0436

Note. Clustered (State) standard-errors in parentheses. *p<0.1; **p<0.05; ***p<0.01. Firm controls include cash flow, capital expenditure, acquisitions (all normalized by assets), market to book ratio, R&D report dummy, log employment, dividend paying status in any given year and industry cash flow volatility. First three column additionally includes state level R&D expenditures and total sales. Last three column uses lag of the baseline controls.

Table 1.4: Sample Adjustments

	Excluding California					
	Cash/Asset	Cash/N.Asset	N.Leverage	Cash/Asset	Cash/N.Asset	N.Leverage
	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
PostEvent	0.0096***	0.0619***	-0.0208***	0.0106***	0.0682***	-0.0246***
	(0.0031)	(0.0224)	(0.0063)	(0.0029)	(0.0224)	(0.0060)
Fixed-effects & Controls						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	Yes	Yes	Yes
Fit statistics						
Observations	12,315	12,315	12,315	12,315	12,315	12,315
R^2	0.85383	0.74574	0.82321	0.86596	0.75359	0.83801
Mean	0.1774	0.4136	0.0766	0.1774	0.4136	0.0766

Note. Clustered (State) standard-errors in parentheses. *p<0.1; **p<0.05; ***p<0.01. Firm controls include cash flow, capital expenditure, acquisitions (all normalized by assets), market to book ratio, R&D report dummy, log employment, dividend paying status in any given year and industry cash flow volatility.

it takes value of 1 if the firm operates in a state passed anti-patent troll law. I consider cash flow, capital expenditures, dividend paying status, acquisition, market to book ratio, R&D Stock to total assets and employment in control and treatment states as explanatory variables to create weights.[47] The balancing table after entropy balancing can be found in

[47] To construct weights, I consider the years before the adoption of the first state law. I simply use the average values of control variables. Results are robust to adding cash/asset ratio as control variable. Instead

Table 1.5: Industry trends

	Industry Trends					
	Cash/Asset	Cash/N.Asset	N.Leverage	Cash/Asset	Cash/N.Asset	N.Leverage
	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
PostEvent	0.0122**	0.1010**	-0.0365***	0.0124***	0.1029**	-0.0243***
	(0.0051)	(0.0435)	(0.0092)	(0.0046)	(0.0411)	(0.0063)
Fixed-effects & Controls						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Industry Trends	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	Yes	Yes	Yes
Fit statistics						
Observations	15,103	15,103	15,103	15,103	15,103	15,103
R^2	0.87021	0.75664	0.83054	0.88048	0.76451	0.79280
Mean	0.2063	0.5216	0.0386	0.2063	0.5216	0.0386

Note. Clustered (State) standard-errors in parentheses. *p<0.1; **p<0.05; ***p<0.01. Firm controls include cash flow, capital expenditure, acquisitions (all normalized by assets), market to book ratio, R&D report dummy, log employment, dividend paying status in any given year and industry cash flow volatility.

Table A.6.4. Results of the estimation using the weights from entropy balancing are given in Table 1.6.

Propensity score reweighting estimator To strengthen the credibility of the results, I also implement a propensity score re-weighting method with difference-in-differences. I calculate the propensity scores similar to Koch et al. (2021). Instead of calculating propensity scores industry by industry, I calculate them in a pooled sample with the industry fixed effects. As in entropy balancing method, I categorize firms into two groups depending on treatment. In particular, I estimated propensity scores by investigating the impact of cash flow, capital expenditures, dividend paying status, acquisition, market to book ratio, R&D Stock to total assets, employment and industry fixed effects on treatment indicator by using the average values of control variables.[48] After estimating propensity scores, I reweigh each treated firm by the inverse of the propensity score, and each control firm by $\frac{1}{1-\hat{p}}$, where $\hat{p}$ is the estimated propensity score. I keep the observations in the region of common support. The balancing table after the re-weighting can be found in Table A.6.5. Results of the estimation using in propensity score re-weighting estimator with difference-in-differences

of considering average of the control variables I also perform entropy balancing method using the initial year, 2010. Results are also robust to this specification. These results are available upon request.

[48]Results are robust to adding average cash/asset ratio (before state-laws) as control variable to calculate propensity scores. Instead of considering average of the control variables I also estimate the propensity scores using the initial year, 2010. Results are also robust to this specification. These results are available upon request. To construct weights, I consider the years before the adoption of the first state law. Unlike **?**, I observe long period of years where PostEvent indicator takes value of 0. Thus, calculating propensity scores using yearly data is not applicable in my case.

Table 1.6: Entropy Balancing

Model:	Cash/Asset (1)	Cash/N.Asset (2)	N.Leverage (3)
Variables			
PostEvent	0.0091***	0.0506***	-0.0217***
	(0.0029)	(0.0165)	(0.0061)
Fixed-effects			
Firm	Yes	Yes	Yes
Year	Yes	Yes	Yes
Fit statistics			
Observations	13,613	13,613	13,613
R^2	0.83173	0.72412	0.81694

Note. Clustered (State) standard-errors in parentheses. *p<0.1; **p<0.05; ***p<0.01.

are reported in Table 1.7.

Table 1.7: Propensity Score Reweighting

Model:	Cash/Asset (1)	Cash/N.Asset (2)	N.Leverage (3)
Variables			
PostEvent	0.0071**	0.0729***	-0.0249***
	(0.0033)	(0.0235)	(0.0071)
Fixed-effects			
Firm	Yes	Yes	Yes
Year	Yes	Yes	Yes
Fit statistics			
Observations	13,600	13,600	13,600
R^2	0.85123	0.74039	0.80681

Note. Clustered (State) standard-errors in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Heterogeneous treatment effects In order to address concerns about biases in two-way fixed effects models caused by heterogeneous treatment effects over time (see e.g., Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021; De Chaisemartin and d'Haultfoeuille, 2020), I revisit the event study approach using the imputation estimator proposed by Borusyak et al. (2022). These results are depicted in Figure A.6.2 in Appendix A.6. My results hold under these additional robustness check.

1.5.2 Financial frictions and Corporate Decisions

In this section I investigate the interplay between introduction of state laws and financial frictions. Similar to Falato et al. (2022), I consider the following financial constraint measures: firm size (total assets and sales), the WW-index Whited and Wu (2006), external finance dependence Rajan and Zingales (1998) and asset liquidity by Berger et al. (1996). Using distribution of these measures, (for each firm I consider the average values of these measures before the introduction of state laws) I separate firms into two groups, as financially constrained and financially non-constrained ones, depending on the median value. I observe that the effect of state law on cash holding and leverage is more pronounced when sample is restricted to a relatively more financially constrained firms. The results are in line with the claims by Chien (2021).

Table 1.8: Effect of the Anti-Patent Trolling Laws on the Cash & Net Leverage: Financial Frictions

	Below Medium			Above Medium		
Measure	Cash/Assets	Cash/Net Assets	N.Leverage	Cash/Assets	Cash/Net Assets	N.Leverage
Asset	0.02015**	0.20716**	-0.06048***	0.00839*	0.03735	-0.01376
	(0.00984)	(0.08892)	(0.01803)	(0.0048)	(0.02403)	(0.01157)
Sales	0.02082***	0.22634***	-0.05349***	0.00723*	0.01823*	-0.01818
	(0.00545)	(0.04757)	(0.01143)	(0.00408)	(0.00958)	(0.01148)
ExFin Index	0.01517**	0.22229***	-0.04124**	0.01238**	0.03352	-0.03112**
	(0.00712)	(0.08099)	(0.01942)	(0.00533)	(0.02796)	(0.01205)
WW-Index	0.01994**	0.10775	-0.055**	0.00911	0.05079**	-0.01511
	(0.00934)	(0.06753)	(0.02177)	(0.0058)	(0.02271)	(0.01245)
Asset Liquidation Value	0.0209***	0.1884***	-0.0644***	0.0048	0.0178	-0.0163
	(0.0047)	(0.0419)	(0.0087)	(0.0051)	(0.0172)	(0.013)

Note. Clustered (State) standard-errors in parentheses. *p<0.1; **p<0.05; ***p<0.01. Firm controls include cash flow, capital expenditure, acquisitions, R&D report dummy, market to book ratio, log employment, dividend paying status in any given year and industry cash flow volatility. Due to the nature of WW-Index and Exfin, the ordering is reversed.

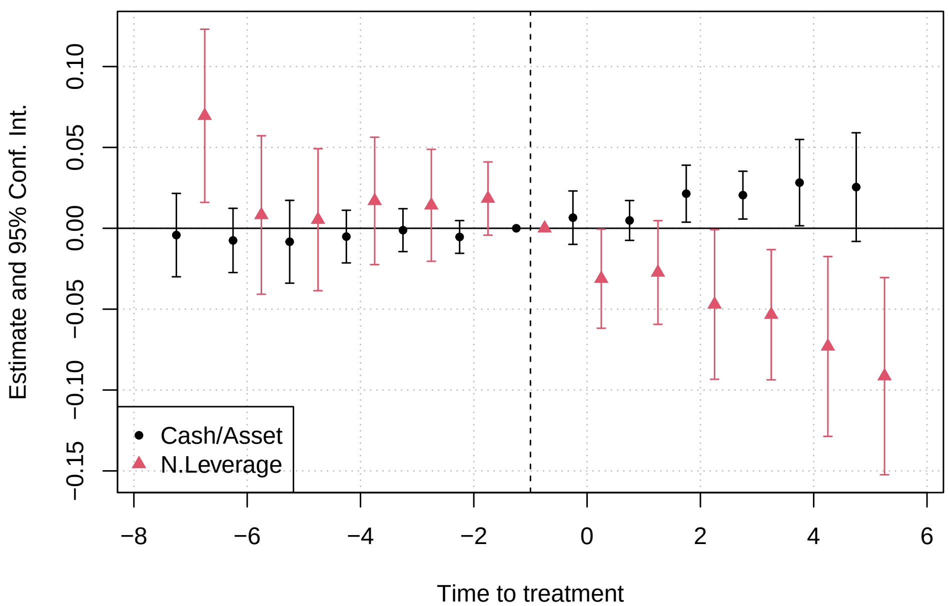
1.6 Alternative Explanations

Intangible capital and Cash Holding Recent literature suggest a positive link between intangible capital and firms' precautionary cash holdings since intangible capital cannot be easily liquidated.[49]. Although the suggested channel is legitimate, e.g., firms with more intangible capital hold more cash, we would expect a credible argument to believe that their change in cash holding with respect to the state laws is driven completely by this channel. In order to claim that the change in the cash holdings is driven mostly by this

[49]See e.g., Falato et al., 2022.

channel, we should expect that the innovative firms operating in states with the laws are affected differently by this channel compared to the firms operating in states without the laws.[50]

Figure 1.7: Cash/Asset and N.Leverage for Innovative Firms



Note. The figure presents the effect of anti-patent trolling laws on firms' cash to asset ratio and net leverage ratio around the years of the anti-patent trolling laws adoption. I estimate equation 1.2 for the innovative firm sample. The intervals around the dots represent 95% confidence intervals. Regressions include firm fixed and year effects and controls. Standard errors are clustered at the state level.

Indeed, if we assume that the introduction of state laws has no effect on cash holdings and that the increase in cash holdings is solely caused by the characteristics of intangible capital, we expect to observe similar changes in the cash holdings of innovative firms regardless of whether they operate in treated or control states. As depicted in 1.5, the impact of state laws are statistically and economically significant when sample is restricted to the innovative firms. In addition, to eliminate the claim that the different responses to the introduction of state laws among innovative are driven mostly by this alternative channel, I check the pre-trends of innovative firms. By utilizing event study design as in 1.2, I observe that after the introduction of state laws, the cash holdings increase and leverage decrease for the innovative firms.[51] Figure 1.7 above shows the results of the event study design for

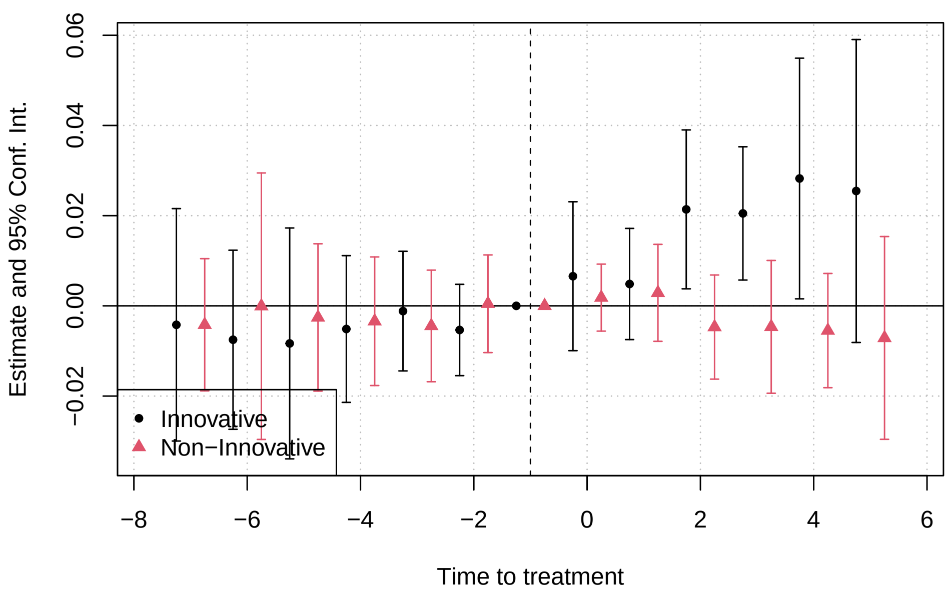
[50] I observe similar results if I separate according to the patent stock status before the state laws or if I consider separating firms according to median level of intangible capital before the state laws.

[51] Note that apart from one of the estimates of net leverage, there is no particular differences between

the innovative firms. Results suggest that the innovative firms in treated and control states are affected differently by the state laws.

I also check the evolution in the corporate decisions of innovative and non-innovative firms with respect to treatment. There is an observed difference between the evolution of cash holdings of innovative and non-innovative firms after the introduction of state laws. Figure 1.8 depicts the results. In the light of this evidence, my results can complement the results of Falato et al. (2022) by providing alternative evidence for the subject.

Figure 1.8: Cash/Asset for Innovative and non-Innovative Firms



Note. The figure presents the effect of anti-patent trolling laws on firms' (separate samples) cash to asset ratio around the years of the anti-patent trolling laws adoption. I estimate equation 1.2 for the innovative firm and non-innovative firm samples. The intervals around the dots represent 95% confidence intervals. Regressions include firm fixed and year effects and controls. Standard errors are clustered at the state level.

Competition As claimed by Bates et al. (2018) the product market competition might have an implication on the marginal value of cash. For product market competition to drive the results, it is expected that it has an impact on corporate decisions. In order to investigate whether the product market competition has an impact on corporate decisions, I first examine the direct impact of HHI. Then, I re-estimate equation 1.2 by interacting time trends with the product market competition measure of Herfindahl-Hirschman index.[52]

innovative firms across treated and control states. The estimates stabilize after this lag.

[52]Since HHI can be defined at the industry level I can not investigate the impact of treatment on HHI. Instead I investigate its interaction with the treatment.

I investigate the direct impact of the product market competition on firms' corporate policies. Table 1.9 presents the results of using HHI as a control variable. The first three columns show results for the full sample and the last three columns show results for the ex-ante innovative firm sample. Results suggest HHI has no statistically or economically meaningful impact on corporate policies.

Table 1.9: Effect of Product Market Competition

	All Sample			Only Innovative Firms		
	Cash/Asset	Cash/N.Asset	N.Leverage	Cash/Asset	Cash/N.Asset	N.Leverage
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
PostEvent	0.0125***	0.1031**	-0.0369***	0.0153**	0.1437**	-0.0554***
	(0.0046)	(0.0410)	(0.0089)	(0.0069)	(0.0650)	(0.0130)
HHI	0.0016	0.1341	0.0131	0.0223	0.2335	-0.0527
	(0.0123)	(0.1131)	(0.0178)	(0.0207)	(0.1685)	(0.0411)
Fixed-effects & Controls						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	15,103	15,103	15,103	8,870	8,870	8,870
R^2	0.88044	0.76452	0.84303	0.87521	0.74552	0.81566
Mean	0.2063	0.5216	0.0386	0.2646	0.7273	-0.0560

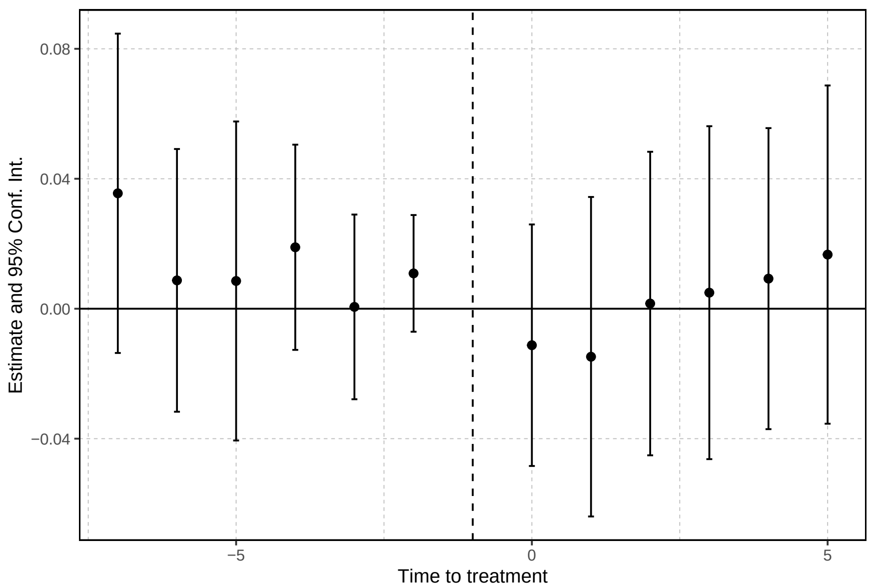
Note. Clustered (State) standard-errors in parentheses. *p<0.1; **p<0.05; ***p<0.01. Firm controls include cash flow, capital expenditure, acquisitions, R&D dummy (all normalized by assets), market to book ratio, log employment, dividend paying status in any given year and industry cash flow volatility.

In addition, I examine the impact of the interaction of treatment with HHI on corporate policies. Figure 1.9 shows the results. Results suggest that the interaction of treatment with HHI has no statistically significant trend before treatment around the treatment period.

External finance dependence As suggested by Bates et al. (2018) and financial constraints can be linked to cash holdings. To be able to eliminate that these channels are important drivers of the baseline results, first, I created yearly external finance dependence category for firms depending on the median level. Then, I perform event study by interacting time trends with the external finance dependence category index. Indeed, if this channel drives the results, we would expect the estimates to show particular differences between the treated and control groups prior to treatment. Additionally, I re-estimate the baseline equation 1.2 by replacing dependent variables with the firm external finance index. These results are depicted in Figure 1.10 below and Figure A.6.3 in Appendix A.6. Results suggest that, before the treatment, there is neither statistically nor economically meaningful differences between treated and control firms.[53]

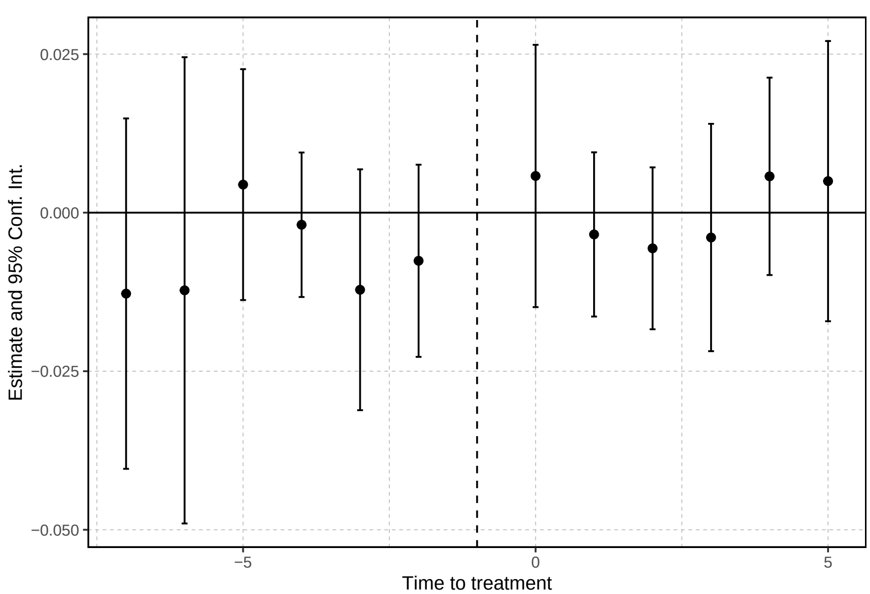
[53] I also perform these analysis with the WW-Index. Results are similar with this specification. These

Figure 1.9: Interaction of treatment with HHI: Impact on cash holding



Note. The figure presents the effect of anti-patent trolling laws on firms' cash to asset ratio around the years of the anti-patent trolling laws adoption. I estimate the equation 1.2 and interact β_τ with the HHI after controlling the baseline β_τ and HHI. The intervals around the dots represent 95% confidence intervals. Regressions include firm fixed and year effects and controls. Standard errors are clustered at the state level.

Figure 1.10: Interaction of treatment with Exfin: Impact on cash holding



Note. The dependent variable is Cash/Asset at the firm level. The omitted category is 1 year before the enactment of the law. The error bars represent 95% confidence intervals. Regressions include firm and year fixed effects and controls. Standard errors are clustered at the state level.

results are available upon request.

1.6.1 Alternative Outcomes

This subsection investigates the effect of state laws on firms' alternative outcomes such as innovation decisions and intangible capital to provide additional evidence in order to support the causal evidence of the baseline analysis.[54] Due to PAEs targeting strategies, investing in innovation might increase the probability of being targeted. In addition, under uncertainty, firms can delay their investments. After the state laws, two channels might alleviate these concerns and impact the innovation decision of firms positively. Table 1.11 presents the results of this investigation. First column present the results for binary R&D uptake while the second column and third column uses R&D expenditure per assets and R&D expenditure in sales as dependent variable. Results suggest that state laws is positively correlated with the firms' R&D decision both at the extensive and intensive margin. I also investigated the impact of state laws on firms intangible capital. Table 1.11 presents

Table 1.10: Effect on R&D

Model:	R&D Uptake (1)	R&D/Assets (2)	R&D/Sales (3)
Variables			
PostEvent	0.0073*	0.0148*	3.339**
	(0.0040)	(0.0088)	(1.424)
Fixed-effects			
Firm	Yes	Yes	Yes
Year	Yes	Yes	Yes
Fit statistics			
Observations	15,103	15,103	15,103
R^2	0.95734	0.79024	0.39024
Mean	0.5357	0.1710	2.138

Note. Clustered (State) standard-errors in parentheses. *p<0.1; **p<0.05; ***p<0.01.

results of this investigation. While the first column presents the impact of state laws on the R&D stock, the second column investigates the impact on organizational stock. The impact on informational capital and intangible capital stock; free of information stock, are presented in column 3 and column 4, respectively. While the impact on informational capital is not statically significant, results also suggest state laws have a positive correlation with the firms' R&D stock and organizational stock.[55]

[54]I also investigate whether firms' employment and labor productivity is affected by state laws. Interestingly, the impact of state laws on labor productivity and employment are statistically and economically insignificant. These results are available upon request.

[55]Since state-law has no impact on informational capital stock, I consider intangible capital as the sum of R&D stock and organizational capital stock. When informational stock is added to intangible capital, the

Table 1.11: Effect on Intangible Capital

	R&D Stock	Org.Stock	Informational Stock	R&D Stock and Org.Stock
Model:	(1)	(2)	(3)	(4)
Variables				
PostEvent	0.0115*	0.0071**	0.0175	0.0186**
	(0.0063)	(0.0036)	(0.0121)	(0.0077)
Fixed-effects				
Firm	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	14,951	14,951	14,951	14,951
R^2	0.89602	0.85077	0.93385	0.87037
Mean	0.2324	0.2211	0.4726	0.4535

Note. Clustered (State) standard-errors in parentheses. *p<0.1; **p<0.05; ***p<0.01. Abnormalities in the R&D stock to asset ratio is dropped from the sample. All of the dependent variables are normalized by the total assets.

1.7 Conclusion

This paper investigates the impact of anti-patent trolling laws on companies' cash and debt policies. I exploit a quasi-natural experiment created by the staggered introduction of state-level anti-patent trolling laws using data of publicly listed firms in the US. I suggest that, after the laws, corporate policies are affected by two opposing channels: decreasing probability of being a potential target for a given cash holding and decreasing uncertainty. Accordingly, I observe that the impact of the decreasing probability of being a potential target dominates the impact of the decreasing uncertainty and increase cash holdings of firms.

I provide four main results. First, I show that firms' cash holdings increased more than 6% and their leverage dropped more than 80% after the passage of the laws. Second, to shed light on the mechanism, I examine the effect of state laws on firms with various levels of innovation. In line with the PAEs targeting strategies, I find that the increase in cash holdings and decrease in leverage are mainly driven by innovative firms. In addition, I highlight the importance of the interplay between financial frictions and uncertainty. I show that the effect of state law on cash holding and leverage is more pronounced when sample is restricted to a relatively more financially constrained firms. Finally, I observe a positive correlation between firms' investment in intangible capital and the introduction

results are statistically insignificant while economically non-negligible.

of state laws.

While many papers in the literature mainly focus on the impact of smaller firms, I provide an alternative perspective to the subject by focusing on relatively bigger firms' corporate policies. The findings presented in this research do not, however, rule out or contradict the possibility that state regulations could be successful in stopping the destructive activities of PAEs and advantageous in particular for small businesses with limited defense capabilities.

There are several venues along which this paper can be extended. First, the impact of state laws on firms' outcomes such as patent applications and venture capital investments can be examined to capture a more comprehensive picture. Second, investigating the impact of state laws on practicing entities' attitude toward patent infringement litigation is another important area of research. It is crucial to understand the motives of practicing entities towards patent litigation and examine whether state laws altered the practicing entities' patent infringement practices. Finally, the concept of this paper can be extended by mostly using data of small firms. The impact of state laws on small firms' corporate policies as well as their hiring and laying of decisions can be examined in detailed.

My results add another layer to the vast literature about cash holdings by providing insight on the effect of the introduction of anti-patent trolling state laws. This paper also has implications for the long lasting discussion about the patent system and PAEs by providing evidence and focusing on firms' corporate policies.

Chapter 2

Patent Ownership, Trade and Lobbying

Abstract This paper examines the participation of firms in lobbying on intellectual property rights when they are exposed to trade shocks. By using the data of publicly listed firms and firm level federal lobbying reports in the US, I first show that patent-owner firms dominate trade lobbying. Then, using the identification strategy of Autor et al. (2013), I establish a causal link between import penetration from China and lobbying on intellectual property rights. Findings suggest that firms increase their lobbying on intellectual property rights as a response to the import penetration from China both at the extensive and intensive margin. Results also highlight the heterogeneous impact on lobbying. Considering existing results on this subject, this paper provides a striking conclusion: Firms facing competition from China prefer lobbying over innovation.

2.1 Introduction

Lobbying activities lie at the intersection of political and economic spheres. Indeed, special interest groups and their representatives play a significant role in the writing process of the bills. Recently, the influence of interest groups draw particular attention due to an observed rise in regulatory complexity and lobbying expenditures (e.g., Gutiérrez, 2019). Recent studies also discuss the depth of trade policies and the importance of non-trade policies such as intellectual property rights.[1] Some studies argue that the firms affect regulations and change them to their advantage (e.g., Kim and Milner, 2018 and Rodrik, 2018). Although there is a vast literature linking trade liberalization to firms' outcomes such as employment[2], the influence of foreign competition on corporations' lobbying activities is

[1]See e.g., Mattoo et al. (2020); Blanga-Gubbay et al. (2023).
[2]See the excellent review by Shu and Steinwender (2019) on this subject.

often disregarded. It is crucial to understand whether firms use lobbying to tackle international competition and its interaction with firms' responses such as innovation.

This paper mainly investigates the impact of import penetration from China on lobbying related to intellectual property rights (IPR).[3] Using firm level federal lobbying reports from Kim (2018), first, I argue that trade lobbying is dominated by the patent-owner firms. Then, I examine the lobbying reaction of firms to increased competition from China for the years between 1999-2007. I establish a causal link between import penetration from China and lobbying on IPR by using the identification strategy of Autor et al. (2013). I also provide results showing the heterogeneous impact on lobbying by separating firms according to their productivity and trade intensity. Finally, this paper links IPR lobbying to trade-related regulations.

The simple OLS estimates would suffer from endogeneity since imports from China might be correlated with demand shocks. In order to overcome this endogeneity concern, I followed the identification strategy of Autor et al. (2013). I simply instrument U.S. imports from China by the imports of eight different countries during the same period.[4]

The import penetration from China affects firms' responses related to innovation via multiple channels. On one hand, firms have more incentive to innovate in response to increased import competition as a way to escape competition. On the other hand, since competition might decrease the rents from innovation, incentive to innovative might decrease.[5] In addition, when subject to trade shocks, firms' motivation to engage in non-market activities depends on the prospective gains and losses from increased competition and its relationship to IPR.[6] Import penetration from China might also create heterogeneity in responses. Indeed, increase in the competition might direct less productive firms to lobby instead of innovation due to high cost associated with innovation activities. However, when exposed to trade shocks, it is expected that firms that have higher stakes in policies related to IPR are more likely to lobby and lobby more. Accordingly, it might be natural to expect that patent-owner firms would lobby more in response to the increasing competition from China.

This study uses multiple data sources. First, I utilize the US Federal lobbying data

[3]There are different types of intellectual property. In this paper IPR refers to the patents, copyrights and trademarks. This limitation is due to the nature of the lobbying reports. The lobbying issue codes for IPR related topics covers Copyright, Patent, and Trademark. The code for this issue is CPT. For simplicity, throughout the paper, I refer lobbying on this issue as IPR. For more information about the issue codes please refer to `https://lda.congress.gov/ld/help/default.htm?turl=Documents%2FAppCodes.htm`.

[4]As in the Autor et al. (2013), I use Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain and Switzerland.

[5]See e.g., Aghion et al., 2005; Shu and Steinwender, 2019.

[6]See e.g., Grossman and Helpman (1994) ; Gawande and Bandyopadhyay, 2000 ; Blanga-Gubbay et al. (2023).

at the firm level. This data is compiled and provided by Kim (2018). It offers detailed information about the lobbying reports. I merge this data with the publicly listed firms in the US from Compustat using firm identifier. I also utilize patent data at the firm level by Arora et al. (2021). Additionally, I gather trade data from UN Comtrade via the World Integrated Trade Solution (WITS) platform. Finally, in Section 2.6, I utilize RegData from Al-Ubaydli and McLaughlin (2017).

I provide multiple results. First, I apply unsupervised topic modelling technique on lobbying reports. I observe that the China appears to be an important part of the lobbying reports before 2007. Then, merging firm level patent data and lobbying data, I show that trade lobbying is dominated by patent-owner firms. I use this results to motivate the next analysis which is based on the impact of the China shock on IPR lobbying. I argue that the firms in the US respond to import penetration from China by increasing their lobbying activities in IPR both at the intensive and at the extensive margin. To eliminate endogeneity concerns, I instrument import penetration from China with the imports of other countries. I observe that 10 percentage points increase in the import share from China increases the probability of lobbying on IPR by 0.6 percentage points and amount of lobbying by 7%. I also provide results showing the heterogeneous impact on lobbying. Finally, I show that when the sample is limited to the firms operating in sectors that are initially less regulated, the relationship between IPR lobbying and China shock is more pronounced.

To strengthen the credibility of the results, I perform robustness checks. First, I consider placebo timing. I use the sample covering the years between 2008 and 2015 as placebo sample.[7] I do not observe any statistically or economically meaningful impact of import penetration from China. In addition, I use lobbying on other issues as a placebo group. For this analysis, I exclude the lobbying on trade and IPR. Results suggest that there is no positive impact of import penetration from China on other issues.

This paper contributes to the many strands of the literature. First, this paper contributes to the empirical lobbying literature.[8] Bombardini and Trebbi (2012) is one of the first studies investigating the relationship between industry characteristics and the mode of lobbying by using federal lobbying expenditures in the US. Their results suggest that sectors with higher level of competition and less concentration are more likely to organize politically and lobby together as a trade association. Bertrand et al. (2004) present evidence to discuss the relative importance of connections versus issue expertise in the US Federal lobbying process. Blanes i Vidal et al. (2012) examines personal connections of ex-government em-

[7]For the baseline analysis, the last year in my sample is 2007 as in Caselli et al., 2021; Autor and Salomons, 2018; Aghion et al., 2021.

[8]See Bombardini and Trebbi (2020) and de Figueiredo and Richter (2014) for excellent reviews of empirical research on lobbying literature.

ployees and the benefits from this channel. Ludema et al. (2018) also investigates political influence of individual firms on congressional decisions by focusing on tariff suspensions on US imports of intermediate goods. Kang (2016) quantifies the impact lobbying expenditures on policy enactment by focusing on all federal energy legislation. Kim (2008) links product differentiation in economic markets to firm-level lobbying in political markets. There are recent studies linking multi-nationality and lobbying. Indeed, Kim and Milner (2018) links multi-nationality of firms to their lobbying expenditures. A recent study by Blanga-Gubbay et al. (2023) shows that large firms in international trade dominate the political economy of free trade agreements and supports the ratification of the free trade agreements. They find out that individual firms spend more to support FTAs that produce larger gains and larger firms spend more to support FTAs. Finally, a recent paper by Bombardini et al. (2021) investigates lobbying responses of firms to increasing competition in US industries. I differentiate my paper from this strand of literature by first establishing a link between firms' patent ownership and trade lobbying. Additionally, I establish a causal connection between import penetration from China and IPR lobbying. Lastly, I establish a connection between trade regulations and IPR lobbying. Consequently, my paper can be viewed as a substitute rather than a complement to the existing literature.

This paper also contributes to the papers investigating the relationship between trade liberalization and firms' outcomes. While many papers examine the impact of trade liberalization on firms' productivity (e.g., Amiti and Konings, 2007; Pavcnik, 2002.), other papers investigate the impact on innovation.[9] Significant share of the papers mainly focus on competition from China. The influential paper by Autor et al. (2013) links Chinese import competition to labor markets. Autor et al. (2020) show that rising import exposure is linked to an increase in competition, decrease in sales, profitability, and R&D expenditure. Bloom et al. (2016) show that the absolute volume of innovation increases with the import penetration from China. Recent papers investigate the impact of penetration of China into the world market using firm level data. For example, Caselli et al. (2021) links labour market imperfections to competition from China using firm level data from France. In addition, Aghion et al. (2021) decompose the China shock into an output and input supply shock. Using firm level data from France, they argue that the output shock negatively affects firms' employment and sales. My paper differentiates from these papers since I focus on the lobbying responses of the firms.

The remainder of the paper is organized as follows. Section 2.2 provides information on the data. Section 2.3 presents empirical strategy. Section 2.4 discusses link between patent ownership and trade lobbying. Section 2.5 presents baseline results. Section 2.6 links trade

[9] See the excellent review by Shu and Steinwender (2019) on this topic.

regulations to IPR lobbying. Section 2.7 concludes.

2.2 Data

This section explains the dataset that is used in this paper. It also provides information on the construction of main variables.

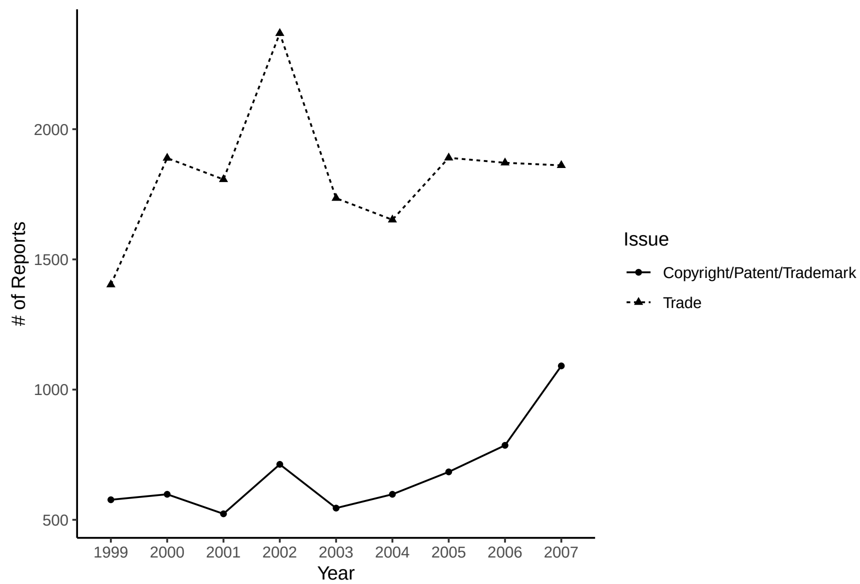
2.2.1 Data Sources

Firm level lobbying data I measure political activity and lobbying by utilizing firm level federal lobbying reports. Due to US Lobbying Disclosure Act (LDA) in 1995, all the reports of federal lobbyists are publicly available and I utilize LobbyView database provided by Kim (2018) to gather organized representation of these lobbying reports. These reports includes detailed information on client firms, lobbyists, summary of the lobbying activity, list of the issues lobbied, report level amount of lobbying and year-quarter of the lobbying activity. LobbyView database also provides firm identifier (gvkey) to merge these lobbying activities to Compustat. One example of the lobbying reports can be found in Figure B.1.1 the Appendix B.3. Lobby reports do not provide a breakdown of the expenditures by issue. Therefore, to calculate the amount of lobbying in the data, I follow the standard procedure in literature (e.g., Ludema et al., 2018; Blanga-Gubbay et al., 2023) and divide the total expenditure of each company equally among the subjects they lobbied for.

Firm level federal lobbying dataset offers one important advantage compared to the campaign contributions data used by early papers related to protection for sale model (e.g., Grossman and Helpman, 1994) such as Gawande and Bandyopadhyay (2000) and Goldberg and Maggi (1999). In contrast to Political Action Committees (PACs) monetary contributions, context of the lobbying reports allows us to detect specific issues that lobbying parties are interested in. In below, Figure 2.1 shows the evolution of the number of trade and IPR related reports over time. We observe an increase in the number of lobbying reports related to trade and IPR.[10]

[10]Note that the lobbying issue code for IPR related topics in the federal lobbying data is CPT. For clarity, throughout the paper, I refer lobbying on this issue as IPR instead of CPT.

Figure 2.1: Number of Lobbying Reports



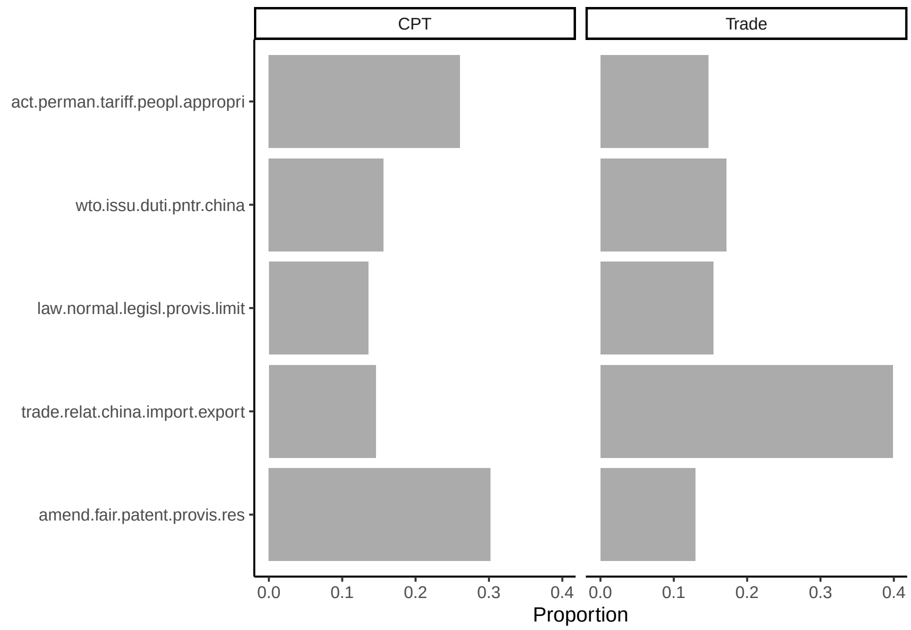
To be able to understand the content of the lobbying activities, I perform text mining techniques on the reports. In particular, I used Latent Dirichlet Allocation to perform topic modelling. For this analysis, I limit the sample to the reports related to trade and IPR. I also limit the sample to the manufacturing firms. I applied topic modelling technique to every year, separately. Figure 2.2 shows the proportion of the topics defined by the five most frequently occurring words for each topic extracted from the text of lobbying. This figure reports only the results for the year 2000.[11] While for the years after the 2007, the appearance of China as an item in any of the topics is limited. For instance, the topic modeling results for the year 2008 can be found in Figure B.2.1 in the Appendix B.2.[12]

As expected, China's penetration in world markets appears to be an important subject in the reports. In addition, import penetration from China is not only important for the trade related lobbying but also IPR related lobbying.

[11] Although the firm level lobbying data is observable since 1999, the text of the lobbying reports is very limited in that year. Therefore, I apply text mining starting from the year 2000.

[12] Results for the rest of the years (graphs), are available on request.

Figure 2.2: Topic Modelling for Trade and IPR Related Reports for 2000



Note. The figure shows the proportion of the topics defined by the five most frequently occurring words for each topic extracted from the text of lobbying. This figure reports only the results for the year 2000.

Compustat I complement lobbying data with the publicly listed firm level data from Compustat. I merge these two dataset by using firm level identifier (gvkey). The standard firm level controls such as employment, sales, fixed assets, R&D expenditures and industry information (SIC) are be observed in Compustat. In the baseline estimations, I control variables that might affect the lobbying activities such as firm size and labor productivity (sales per worker). I also constructed the HHI using the sales of the firms for each industry(SIC)-year group. Finally, I created a variable in line with the Kim and Milner (2018) to measure whether firm is multinational or not. Using firm's pretax foreign income (pifo), I created binary variable that takes value of 1 if pretax foreign income is reported. I limit my sample to the manufacturing firms and years between 1999-2007 in line with the papers investigating the impact of import penetration from China.[13] I perform standard cleaning procedures. I keep the firms reporting positive levels of employment,sales and total assets. I drop top and bottom one percent of the employment, sales and total assets distribution to exclude abnormalities. All monetary values are deflated and stated in 2015 dollars.

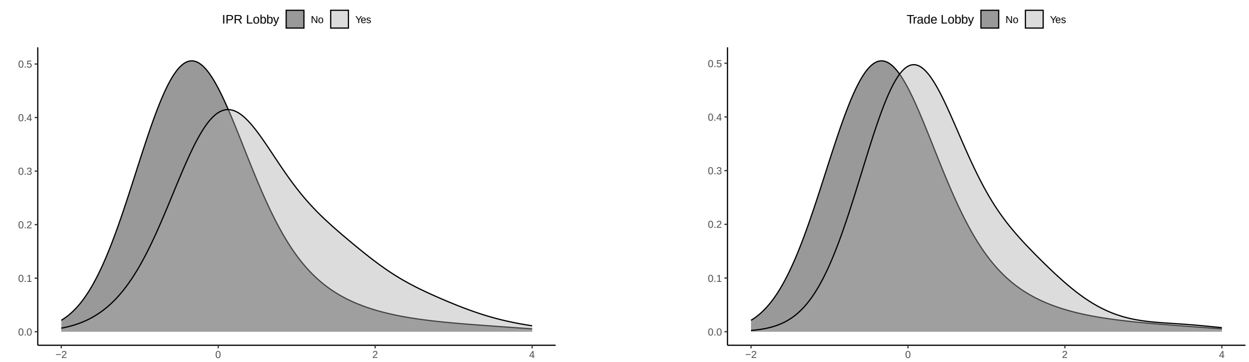
Patent Data To be able to observe patent data at the firm level, I utilize the dataset provided by Arora et al. (2021). This dataset provides an patent stocks and yearly patent

[13] See e.g., Autor and Salomons, 2018; Caselli et al., 2021; Aghion et al., 2021.

numbers of the firms by considering dynamic reassignment, name and ownership changes. I merge Compustat and the firm level patent with the unique firm level identifier (gvkey).

Trade Data I obtain the trade data between China and the US from UN Comtrade Database via WITS platform. I also gather trade data for the countries used to calculate instrument. This data gives the value of the bilateral trade at the six-digit HS level. I map these HS level codes to 4 digit-SIC codes using concordance tables from Schott (2008).

Figure 2.3: Firm Productivity and Lobbying



(a) Labor Productivity-IPR

(b) Labor Productivity-Trade

Note. Panel (a) depicts the distribution of standardized labor per worker with IPR lobbying separation. Panel (b) shows the same as panel (a) using standardized labor per worker with respect to trade lobbying.

Before turning to the analysing, I provide graphical evidence on the relationship between firm productivity and Trade-IPR lobbying. Panel (a) of Figure 2.3 plots the distribution of deflated and standardized labor productivity for firms lobby IPR vs firms do not lobby IPR. The figure reveals that the distribution of firms lobbying IPR is slightly shifted to the right compared to the distribution of firms that do not lobby IPR. Since I compute the measure of labor productivity relative to the year mean, differences in firm labor productivity across years are not driving this observation. Panel (b) of Figure 2.3 plots the distribution of labor productivity with respect to trade lobbying. Similar pattern is observed in the distribution of labor productivity with respect to trade lobbying.[14]

The Table 2.1 presents the summary statistics from the sample. The sample period covers the years between 1999–2007. The lobbying variables refers to the IPR related lobbying under the issue code covering Copyright, Patents and Trademark (CPT). The amount of lobbying is in thousands of 2015 dollars.

[14]These patterns are similar if sales values are used instead of labor productivity.

Table 2.1: Summary Statistics

Statistic	N	Mean	St. Dev.	Median	P25	P75
Log(Emp)	14,668	6.043	1.957	5.861	4.585	7.502
Log(Sale)	14,668	18.308	2.322	18.365	16.725	19.989
Log(Assets)	14,668	18.678	2.049	18.660	17.239	20.157
Log(Sale/Emp)	14,668	12.265	0.833	12.360	11.933	12.754
Foreign-Income(Binary)	14,668	0.261	0.439	0	0	1
HHI	14,668	0.223	0.175	0.173	0.111	0.259
Patent Stock	14,668	40.098	236.950	2.801	0.000	15.551
Patent (Yearly)	14,668	9.342	55.543	0.000	0.000	4.000
Lobby Amount	14,668	3.409	63.411	0.000	0.000	0.000
Lobby(Binary)	14,668	0.013	0.111	0	0	0
of Reports	14,668	0.032	0.377	0	0	0
China Import Share	14,668	0.095	0.133	0.045	0.008	0.125
Import Share (Instrument)	14,668	0.070	0.099	0.033	0.005	0.096
Export Share	14,668	0.027	0.026	0.019	0.006	0.038

Note. Summary statistics. This table reports the summary statistics of the main variables. The sample period covers the years between 1999–2007. The lobbying variables refers to the IPR related lobbying under the issue code covering Copyright, Patents and Trademark (CPT).The amount of lobbying is in thousands of 2015 dollars.

2.3 Empirical Strategy

In this section, I discuss the empirical strategy. Using instrumental variable strategy, I estimate the impact of import penetration from China on firms' lobbying related to IPR. In all of these specifications, I consider the the binary lobbying variable which takes value of 1 if firm lobby on the particular subject at time t, zero otherwise. I also consider the number of reports for a particular subject at time t and the amount of lobbying. The amount of lobbying refers to the firms' total amount of lobbying in particular subject at time t. To include firms with zero lobbying amount, I add one and use log of the lobbying amount. Formally, I consider the following equation.

$$Y_{i,j,t} = \mu_j + \gamma_t + \beta ImportShare_{j,t} + +\delta \mathbf{X}_{i,t} + \epsilon_{i,j,t} \tag{2.1}$$

where $Y_{i,j,t}$ is one of the following variables: lobbying (binary), number of reports, and amount of lobbying for firm i in industry j time t.[15] μ_j and γ_t are the sector (SIC, 4-digit) and year fixed effects. $ImportShare_{j,t}$ is the share of the imports from China in total import of US for sector j time t. Finally, $\mathbf{X}_{i,t}$ denotes for the firm controls such as firms' log employment, log sales per worker, HHI, log patent stock[16], binary indicator takes value

[15] I use the log of (1+ lobbying expenditure) to be able to include zero expenditures.

[16] To include non-patent owner firms to the sample, I add one to the patent levels.

of 1 if firm lobbies on other issues at time t, binary variable for foreign income, industry-year level export share of US to China and the log of the rest of the employment in the industry.[17] β main variable of interest and it is expected to have positive sign.

The baseline estimation suffers from endogeneity since β also might simply reflect the increase in the U.S. demand. To focus on the supply-shock from China, following Autor et al. (2013), I instrument U.S. import share from China with imports share of eight different countries, during the same period. As in Autor et al. (2013), these countries are Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain and Switzerland.[18]

2.4 Patent Ownership and Trade Lobbying

In this section, I briefly investigate the relationship between trade lobbying and patent-ownership. I show that the patent-owner firms dominate the trade lobbying. I consider this section to motivate my results for the baseline analysis. Since patent-owner firms dominate trade lobbying, under a competition shock it is expected to observe increase in the lobbying related to IPR.

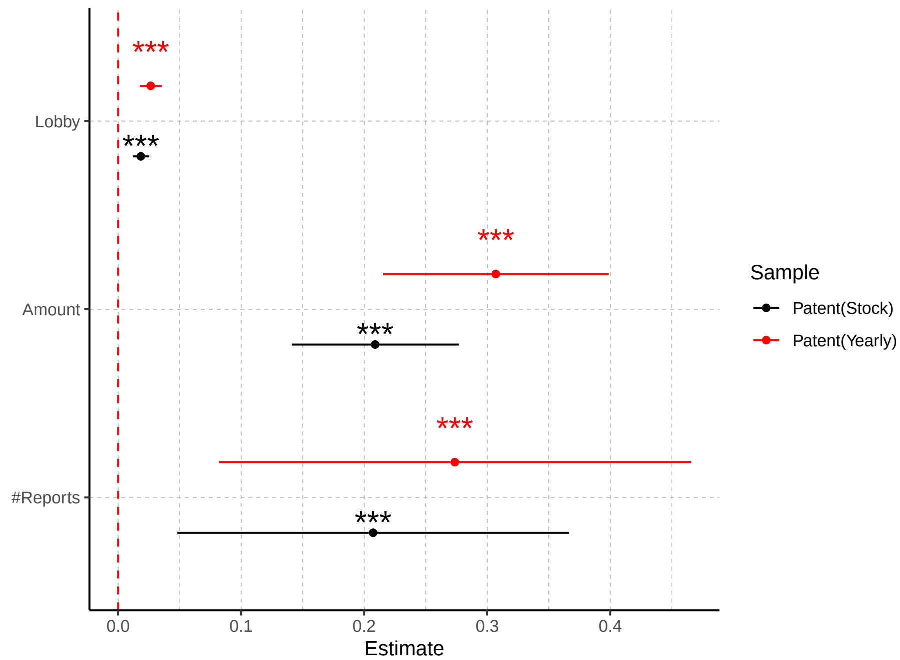
In this section, I use a similar model that is presented in Section 2.3. Instead of considering IPR lobbying on the right hand side, I collapse the trade and tariff related lobbying reports to the firm and year level. For each firm, I observe the lobbying (binary), number of reports and log amount of lobbying each year. To include firms with zero lobbying amount, I add one and use log of the lobbying amount. The key variable of interest in this section is coefficient of the patent levels. I consider two different patent measures from Arora et al. (2021): yearly patent levels and patent stocks. To include non-patent owner firms in the sample, I add one to the patent measures and take logs. Figure 2.4 presents the results of these estimation. All of the controls explained in the Section 2.3 included in this estimations. Instead of including import share from China and export share of US to China, I control overall import and export shares in the total industry sales. The standard error are clustered at the 3-digit industry level (SIC3). The red line in Figure 2.4 depicts the estimates for yearly patent variable while the black line shows the estimates for yearly patent stock.

Results suggest that the patent-owner firms dominate the trade lobbying. This results are also in line with recent discussions centered around the deep trade agreements (e.g.,

[17] Although, the rest of employment, and HHI is at the industry level (SIC), for the brevity of the notation I include them in the firm controls.

[18] The discussion of the validity of the instrument is discussed in Autor et al. (2013) and Autor et al. (2016).

Figure 2.4: Patent Ownership and Trade Lobbying



Note. The figure presents the effect of patents on firms' lobbying on trade. Standard errors are clustered at the 3-digit industry level (SIC3).

Mattoo et al., 2020; Rodrik, 2018; Blanga-Gubbay et al., 2023). In addition, results in this section might suggest that firms might have more incentives to lobby on IPR when they are exposed to a trade shock.

2.5 Import Penetration from China and IPR Lobbying

In this section, I, first, report the impact of import share from China on the IPR lobbying without using instrumental variable. Then, I present the results of instrumental variable model using eight different countries imports as an instrument.

Results of the baseline estimation is presented in the Table 2.2. First column of Table 2.2 presents results for the extensive margin. 10 percentage points increase in the import share from the China is associated with 0.4 percentage points increase in lobbying on IPR. While this number is equal to 4% for the amount of lobbying. The results without the control variables can be found in Table B.3.1 in the Appendix B.3. I also consider probit estimation instead of OLS for binary lobbying. These results can be found in the first column of Table B.3.2 in Appendix B.3. First column of Table B.3.2 shows the probit estimation without the instrument while the second column reports the estimates where import share is instrumented.

Table 2.2: Import Penetration from China and IPR Lobbying

Model:	Lobby(Binary) (1) OLS	#Reports (2) Poisson	Amount (3) OLS
Variables			
ImportShare	0.0425**	2.184***	0.4344**
	(0.0164)	(0.6837)	(0.1975)
Fixed-effects & Controls			
SIC	Yes	Yes	Yes
Year	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Fit statistics			
Observations	14,668	8,823	14,668
R^2	0.11948		0.11928
Pseudo R^2		0.58783	

Note. Clustered (SIC3) standard-errors in parentheses. *p<0.1; **p<0.05; ***p<0.01. Firm controls include log employment, log sales per worker, HHI, log patent stock, binary indicator takes value of 1 if firm lobbies on other issues at time t, binary variable for foreign income, industry-year level export share of US to China and the log of the rest of the employment in the industry.

Instrumental variable estimates are given in Table 2.3. I observe that 10 percentage points increase in the import share from China increases the probability of lobbying on IPR by 0.6 percentage points and amount of lobbying by around 7%. As before first column reports the estimates for binary lobbying while the second and third columns reports results for the intensive margin measures.[19] First stage coefficients also reported under the Table 2.3. These coefficients are statistically significant and economically meaningful. Kleibergen-Paap Wald F statistics are reported under the Table 2.3 which eliminates the weak instrument concerns.

The coefficients with the instrumental variable model is relatively higher compared to OLS coefficients.[20] Downward bias observed in OLS estimates might suggest a possibility of reverse causality. In particular, this might suggest that the lobbying can have a negative effect on Chinese imports. Considering results of Autor et al. (2020), these results suggests that firms in USA favor lobbying over innovation as a response to increasing competition from China.[21]

[19]Rather than focusing on manufacturing firms, I also consider firms from all sectors. These results can be observed in the the Table B.3.3 in Appendix B.3

[20]Only the coefficient of number of reports is slightly higher in the OLS.

[21]I also consider the impact of China shock on trade related lobbying. Not surprisingly, the results suggest a positive impact of the China's import penetration on trade lobbying both at the extensive and intensive margin. I also investigate the lobbying on other issues. Results suggest that for most of the subjects the impact of China shock is statistically and economically insignificant. However, there are a small of amount of subjects where the import penetration from China has a positive impact on lobbying (e.g., consumer issues,

Table 2.3: Import Penetration from China and IPR Lobbying: Instrumental Variable

Model:	Lobby(Binary) (1)	#Reports (2)	Amount (3)
Variables			
ImportShare	0.0659***	1.776*	0.7338***
	(0.0213)	(0.9479)	(0.2562)
Fixed-effects & Controls			
SIC	Yes	Yes	Yes
Year	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Fit statistics			
Observations	14,668	8,823	14,668
R^2	0.11965		0.11948
Pseudo R^2		0.58737	
	First-Stage Estimates		
Coef.-Instrument	1.0544***	1.0636***	1.0544***
	(0.0338)	(0.0304)	(0.0338)
F-test (1st stage)	971.8	166.8	971.8

Note. Clustered (SIC3) standard-errors in parentheses. *p<0.1; **p<0.05; ***p<0.01. Firm controls include log employment, log sales per worker, HHI, log patent stock, binary indicator takes value of 1 if firm lobbies on other issues at time t, binary variable for foreign income, industry-year level export share of US to China and the log of the rest of the employment in the industry.

Heterogeneous Impact I also investigate heterogeneous impact on lobbying. Figure 2.5 reports the estimates from OLS with separating into sample into two groups for the extensive margin. Firms are labeled as productive if their sales per worker ratio is higher than the median productivity level of their sector j at time t. I observe that the results on the extensive margin is driven by the relatively more productive firms. Results suggest that the more productive firms are more likely to lobby on IPR while the impact for the non-productive firms neither statistically nor economically meaningful.

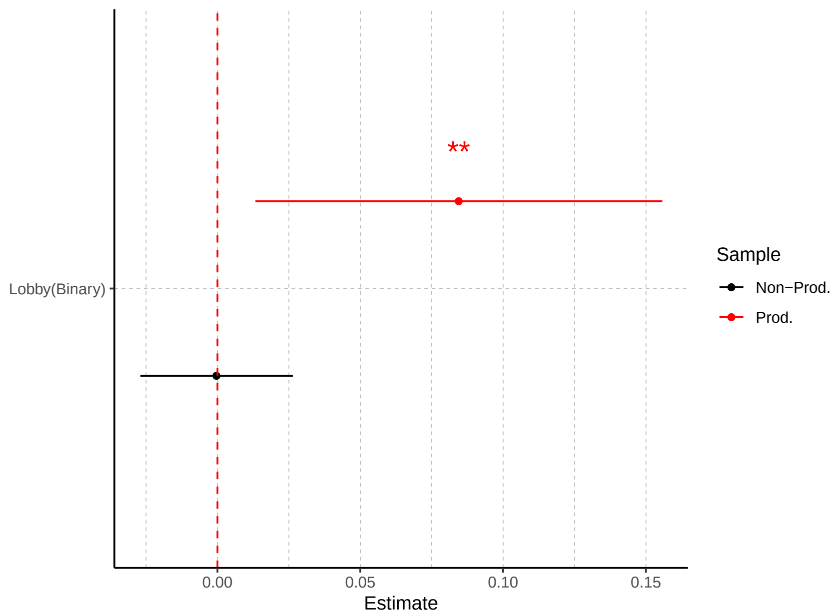
I also investigate the impact on the intensive margin. Figure 2.6 presents these results. Similar to extensive margin, more productive firms lobby more on IPR.[22] Results at the extensive and intensive margin can be justified with the stakes in lobbying and fixed cost of lobbying. Since firms' incentive to participate lobbying activities depends on the potential impact of China's penetration on IPR related issues, it is natural to expect that firms with sufficiently high stakes in lobbying are more likely to lobby and they lobby more.

Additionally, it is natural to expect that firms more intensively exposed to import penetration from China, lobby more. I investigate this claim by separating the industries into

safety and protection).

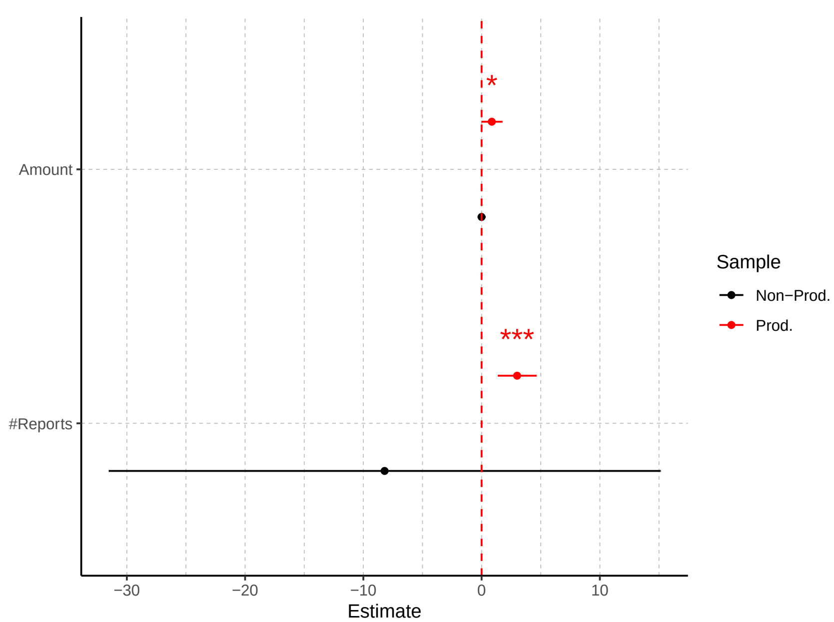
[22]Note that due to graphical representation the confidence interval for the report variable of non-productive firms are not depicted well. These results can be found in the Table B.3.4 in Appendix B.3.

Figure 2.5: Extensive Margin: Lobbying and Productivity



Note. The figure presents the estimates from OLS with separating into sample into two groups (firm productivity) for the extensive margin. I follow the baseline specification in 2.1 with control variables.

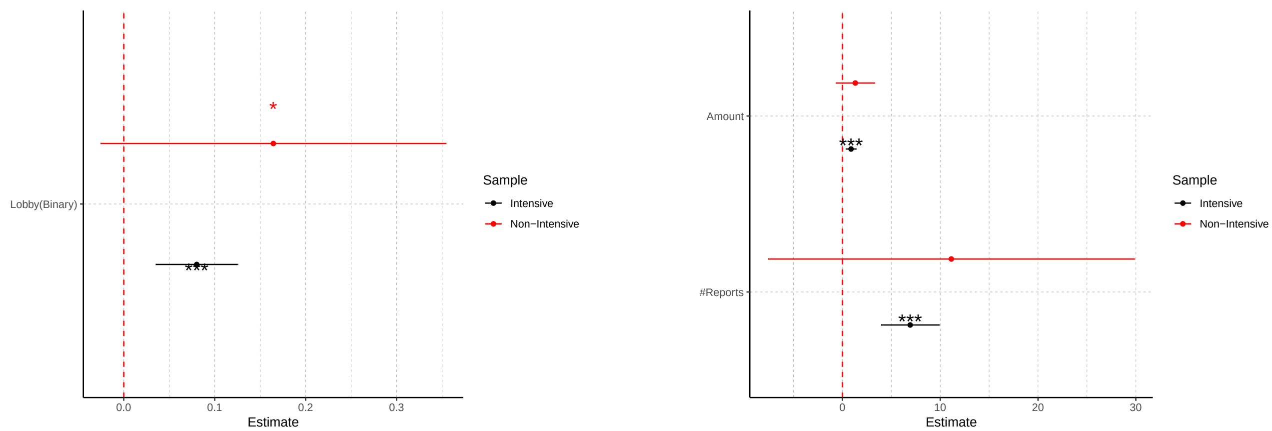
Figure 2.6: Intensive Margin: Lobbying and Productivity



Note. The figure presents the estimates from OLS with separating into sample into two groups (firm productivity) for the intensive margin. I follow the baseline specification in 2.1 with control variables.

two group depending on their import shares. Industries are labelled as intensive if their import share from China is higher than the median import share at time t. Figure 2.7 reports the estimates from OLS with separating into sample into two groups.

Figure 2.7: Non Intensive vs Intensive Import Penetration from China



Note. Panel (a) presents the estimates from OLS with separating into sample into two groups (trade intensity) for the extensive margin. Panel (b) presents the estimates from OLS with separating into sample into two groups (trade intensity) for the intensive margin. I follow the baseline specification in 2.1 with control variables.

Indeed, I observe that the firms operating in industries that are more intensively exposed to import penetration from China are more likely to lobby and lobby more on IPR. Corresponding estimates from instrumental variable specification are reported in the Table B.3.5 and Table B.3.6 in Appendix B.3.

2.5.1 Robustness Checks

Placebo Timing In order to strengthen the credibility of the results, I consider placebo timing. In line with the literature, I consider the period before 2007 for the baseline analysis.[23] I claim that the impact of the import penetration from China is expected to be more pronounced for the period before 2007. To check this claim, I limit my sample to the period between the years 2008-2015 for the placebo timing analysis. Table 2.4 present this results. Results suggest that there is no statistically meaningful impact of import penetration from China.

Placebo Group I also consider placebo group. As a placebo outcome, I consider lobbying on other issues excluding trade and IPR related reports. Then, I aggregate lobbying amounts, binary lobbying behaviour and number of reports to the firm and year level. Table 2.5 presents this results. Results suggest that there is no statistically significant impact

[23] See e.g., Autor et al., 2013; Aghion et al., 2021; Caselli et al., 2021.

Table 2.4: Import penetration from China and IPR Lobbying:Placebo Timing

Model:	Lobby(Binary) (1) OLS	#Reports (2) Poisson	Amount (3) OLS
Variables			
ImportShare	-0.0183	2.174	-0.1800
	(0.0583)	(5.359)	(0.6084)
Fixed-effects			
SIC	Yes	Yes	Yes
Year	Yes	Yes	Yes
Controls	No	No	No
Fit statistics			
Observations	9,378	5,963	9,378
R^2	0.19576		0.18929
Pseudo R^2		0.65181	

Note. Clustered (SIC3) standard-errors in parentheses. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

of import share.[24]

Import Penetration from the Free Trade Agreement Partners In order to strengthen the results, I also consider an alternative import penetration measure. To claim that the increase in IPR lobbying is specific to China import penetration, I consider the import penetration from the Free Trade Agreement (FTA) partners of the US[25]. Table 2.6 presents these results. Results suggest that the import penetration impact on IPR lobbying can not be explained by the other trade partners.

Export Penetration to China The increase in the IPR lobbying might be linked to the US export penetration to the China in addition to the China import penetration. To control these channel, in the main estimation, I add US export share to China as a control variable in the estimations. However, in this part, I consider the export penetration from US as a main variable of interest and instrument this variable with the export penetration of eight different countries to China.[26] Table 2.7 presents these results. Results suggest that the results are not driven by the export penetration of the US to China.

[24]As an alternative robustness check, I also consider another placebo group and exclude a couple of issues where import penetration from China has a positive impact, such as (e.g., consumer issues, safety and protection). Then I investigate the impact of import penetration from China on lobbying. Results suggest that there is no statistically significant impact of China import share. These results are available upon request.

[25]FTA partners of the US are Australia, Bahrain, Chile, Costa Rica, Dominican Republic, El Salvador ,Guatemala, Honduras, Jordan, Morocco, Nicaragua, Oman, Peru, Singapore.

[26]I consider the same countries as in baseline.

Table 2.5: Import Penetration from China and Placebo Group

Model:	Lobby(Binary) (1) OLS	#Reports (2) Poisson	Amount (3) OLS
Variables			
ImportShare	-0.0824	0.5273	-1.216
	(0.0515)	(0.3261)	(0.9399)
Fixed-effects			
SIC	Yes	Yes	Yes
Year	Yes	Yes	Yes
Controls	No	No	No
Fit statistics			
Observations	14,668	13,609	14,668
R^2	0.10050		0.10567
Pseudo R^2		0.23646	

Note. Clustered (SIC3) standard-errors in parentheses. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table 2.6: Import Penetration from FTA Partners and IPR Lobbying

Model:	Lobby(Binary) (1) OLS	#Reports (2) Poisson	Amount (3) OLS
Variables			
ImportShare(FTA Partners)	-0.0454	-4.187	-0.2148
	(0.0345)	(2.554)	(0.4307)
Fixed-effects			
SIC	Yes	Yes	Yes
Year	Yes	Yes	Yes
Controls	No	No	No
Fit statistics			
Observations	14,668	8,823	14,668
R^2	0.03538		0.03515
Pseudo R^2		0.10662	

Note. Clustered (SIC3) standard-errors in parentheses. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table 2.7: Export Penetration of USA and IPR Lobbying

Model:	Lobby(Binary) (1) OLS	#Reports (2) Poisson	Amount (3) OLS
Variables			
Export Share	-0.0328	2.607	-0.3491
	(0.1333)	(6.804)	(1.388)
Fixed-effects & Controls			
SIC	Yes	Yes	Yes
Year	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Fit statistics			
Observations	14,668	8,823	14,668
R^2	0.11922		0.11908
Pseudo R^2		0.58700	
	First-Stage Estimates		
Coef.-Instrument	0.5099***	0.6396***	0.5099***
	(0.1003)	(0.1449)	(0.1003)
F-test (1st stage)	25.83	11.96	25.83

Note. Clustered (SIC3) standard-errors in parentheses. *p<0.1; **p<0.05; ***p<0.01. Firm controls include log employment, log sales per worker, HHI, log patent stock, binary indicator takes value of 1 if firm lobbies on other issues at time t, import penetration of China, binary variable for foreign income and the log of the rest of the employment in the industry.

2.5.2 Importance of IPR Lobbying

In this section, I investigate the importance of IPR in total lobbying activities, by limiting the sample to the firms that participate in lobbying activities at time t.[27] Before, I move to the analysis I first replicate the baseline impact by restricting the sample to the firms lobbied at least one issue at a particular time.

Table 2.8 presents the results limiting the sample to the firms lobbied at least one issue. Results suggest that the baseline outcomes not solely driven by the non-lobby participant firms. The first three columns of Table 2.8 presents the OLS results while the last three columns presents the estimates from instrumental variable specification.

Table 2.8: Firms Lobbied on at Least One Issue

Model:	Lobby(Binary) (1) OLS	#Reports (2) Poisson	Amount (3) OLS	Lobby(Binary) (4) IV	#Reports (5) IV	Amount (6) IV
Variables						
ImportShare	0.2986***	2.169***	2.900***	0.4438***	1.711*	4.917***
	(0.0954)	(0.6948)	(1.018)	(0.1219)	(0.9157)	(1.339)
Fixed-effects & Controls						
SIC	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	1,897	1,350	1,897	1,897	1,350	1,897
R^2	0.25663		0.26516	0.25761		0.26640
Pseudo R^2		0.40504			0.40426	
			First-Stage Estimates			
Coef.-Instrument				1.0782***	1.0812***	1.0782***
				(0.0415)	(0.0553)	(0.0415)
F-test (1st stage)				675.5	73.76	675.5

Note. Clustered (SIC3) standard-errors in parentheses. *p<0.1; **p<0.05; ***p<0.01. First three columns reports estimates without the control variables while the last three column includes controls. Firm controls include log employment, log sales per worker, HHI, log patent stock, binary variable for foreign income, industry-year level export share of US to China and the log of the rest of the employment.

To highlight the importance of IPR lobbying (in total lobbying of each firm-year group) for the firms engaged in non-market strategies, I also consider the share of IPR lobbying in total lobbying amount (reports) instead of the levels of the amount (the number of) lobbying. Table 2.9 presents the results.[28]

First two columns of Table 2.9 reports estimates without the control variables while the last two column includes controls. Results suggest that firms engaged in lobbying ac-

[27] In particular, I consider firms that lobbied at least one issue at time t.

[28] For each firm at time t I calculate the share of IPR lobbying as the ratio of the amount of IPR lobbying in total lobbying. Share of report numbers calculated in same way.

Table 2.9: Share of IPR Lobbying

Model:	Share Amount IPR (1)	Share Report IPR (2)	Share Amount IPR (3)	Share Report IPR (4)
Variables				
ImportShare	0.1353**	0.1524***	0.2117***	0.2288***
	(0.0523)	(0.0511)	(0.0346)	(0.0424)
Fixed-effects & Controls				
SIC	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Fit statistics				
Observations	1,897	1,897	1,897	1,897
R^2	0.22729	0.21099	0.22663	0.21035
		First-Stage Estimates		
Coef-Instrument			1.0782**	1.0782**
			(0.0324)	(0.0324)
F-test (1st stage)			1,105.0	1,105.0

Note. Clustered (SIC3) standard-errors in parentheses. *p<0.1; **p<0.05; ***p<0.01. First two columns reports estimates without the control variables while the last two column includes controls.Firm controls include log employment, log sales per worker, HHI, log patent stock, binary indicator takes value of 1 if firm lobbies on other issues at time t, binary variable for foreign income, industry-year level export share of US to China and the log of the rest of the employment.

tivities, not only increased the level of amounts/reports of lobbying but also the share of lobbying activities in total non-market activities. Results in column 3 suggest that the 10 percentage points increase in the import penetration from China increases the share of reports and amount of lobbying related to IPR by almost 2 percentage points. Kleibergen-Paap Wald F statistics are reported under the table and rule out the weak instrument concerns. Interestingly, I do not observe the same pattern when IPR lobbying share is replaced with the trade lobbying shares. These evidences might suggest that firms value IPR lobbying more than trade lobbying for the period between 1999-2007.

2.6 Regulations and Lobbying

In this section, I investigate whether the level of trade regulation in an industry plays a role in lobbying on intellectual property rights. In order to construct the level of trade regulation in an industry, I use RegData from Al-Ubaydli and McLaughlin (2017). Utilizing text analysis, Al-Ubaydli and McLaughlin (2017) quantifies the restrictive limitations in Code of Federal Regulation by industry and by regulatory agency. They provide regulation for industries at various levels of the North American Industry Classification System (NAICS).

Particularly, utilizing agency information, I, first, construct industry level regulation index related to trade for 1998 at the 4 digit NAICS. After merging this data to my sample over industries, I separate industries into two groups according to the median level of trade regulation index. Finally, I estimate the baseline equation 2.1 for these two different samples. I show that the link between IPR lobbying and China shock is more pronounced when sample is restricted to the firms operating in industries that are initially less regulated. The Table 2.10 presents these results. The first three columns shows the results for the firms operating in initially less regulated industries while the last three columns present the results for the rest.

Table 2.10: Trade Regulations and IPR Lobbying

	Less Regulated			More Regulated		
	Lobby(Binary)	#Reports	Amount	Lobby(Binary)	#Reports	Amount
Model:	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	Poisson	OLS	OLS	Poisson	OLS
Variables						
ImportShare	0.0772***	5.352**	0.7832***	0.0417	4.630	0.5387
	(0.0221)	(2.301)	(0.2422)	(0.0281)	(4.994)	(0.3320)
Fixed-effects & Controls						
SIC	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	6,306	3,672	6,306	8,307	4,083	8,307
R^2	0.13575		0.13943	0.11019		0.11188
Pseudo R^2		0.58364			0.61617	

Note. Clustered (SIC3) standard-errors in parentheses. *p<0.1; **p<0.05; ***p<0.01. The first three columns shows the results for the firms operating in initially less regulated industries while the last three columns present the results for the rest. Firm controls include log employment, log sales per worker, HHI, log patent stock, binary indicator takes value of 1 if firm lobbies on other issues at time t, binary variable for foreign income, industry-year level export share of US to China and the log of the rest of the employment.

I also consider corresponding instrumental variable as in Section 2.5. The 2.11 presents instrumental variable model results. As before, I observe an increase in the coefficient of binary lobbying and the amount of lobbying on IPR when IV specification is used. These findings can be considered as supporting evidence for the papers that exploring the depth of trade policies.[29] However, it is important to highlight that these results do not provide any insight on the aim of the lobbying activity related to the regulations.

[29]See e.g., Mattoo et al. (2020); Blanga-Gubbay et al. (2023).

Table 2.11: Trade Regulations and IPR Lobbying (Less Regulated): Instrumental Variable

Model:	Lobby(Binary) (1)	#Reports (2)	Amount (3)
Variables			
ImportShare	0.0846***	3.678	0.8793***
	(0.0266)	(2.865)	(0.2781)
Fixed-effects & Controls			
SIC	Yes	Yes	Yes
Year	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Fit statistics			
Observations	6,306	3,672	6,306
R^2	0.13557		0.13932
Pseudo R^2		0.58168	
Coef.-Instrument	0.9657***	1.0126***	0.9657***
	(0.0531)	(0.0695)	(0.0531)
F-test (1st stage)	330.7	104.7	330.7

Note. Clustered (SIC3) standard-errors in parentheses. *p<0.1; **p<0.05; ***p<0.01. Firm controls include log employment, log sales per worker, HHI, log patent stock, binary indicator takes value of 1 if firm lobbies on other issues at time t, binary variable for foreign income, industry-year level export share of US to China and the log of the rest of the employment.

2.7 Conclusion

This paper mainly investigates the impact of competition from China on lobbying related to IPR. By using the data of publicly listed firms and firm level federal lobbying reports in the US, I first perform unsupervised topic modelling on lobbying reports. I observe that the China appears to be an important part of the lobbying reports. Then I show the link between patent ownership and lobbying on trade to motivate the baseline analysis. Finally, I establish a causal link between import penetration from China and IPR lobbying.

I provide three main results. First I show that patent-owner firms dominate trade lobbying. Second, I demonstrate that firms are more engaged in lobbying on intellectual property rights (IPR) when they are exposed to trade shocks. Using the identification strategy of Autor et al. (2013), I establish a causal link between import penetration from China and IPR lobbying. According to the findings, firms are increasing their lobbying on intellectual property rights in response to Chinese import penetration. The findings also highlight the heterogeneous impact on lobbying. I claim that the along with the existing evidences on this subject e.g., Autor et al. (2020), this paper suggests that firms in the US favor lobbying over innovation as a response to increasing competition from China. Finally, I also link trade regulations to the IPR lobbying.

There are multiple venues along which this paper can be extended. First, this paper can be extended to examine the impact of import penetration from China on campaign contributions. In addition, instead of considering only patent-ownership this study can also be extended to include trademarks and copyrights. Finally, the impact of China's trade shock can be investigated by classifying the purpose of lobbying using lobbying reports.

My results add another layer to the vast literature connecting trade shocks and firm responses by particularly focusing on the non-market responses of the firms. It also delivers a startling conclusion: As response to competition from China, corporations prioritizing lobbying over innovation.

Chapter 3

Technological Innovation, Digital Adoption and Firm Performance

Abstract This study investigates the impact of digital technology adoption on various firm outcomes. Using the Investment Survey of the European Investment Bank (EIBIS), we first show that the large and productive firms adopt digital technologies. To address the impact of adopting digital technologies on firms' outcome, we develop instruments that combine input-output linkages between country-industry groups and sector-specific digital patent stocks. Results suggest that the digital technology adoption leads to a significant increase in productivity and wages. In addition, we observe that digital technologies positively affect firms' training decisions and management practices as well as their investment in innovation. We also present a positive causal effect of digital technology adoption on firms' outcome by using difference-in-differences technique with a propensity score matching.

3.1 Introduction

Recent advances in digital technologies accelerated the discussions about the economic consequences of adopting these technologies. A major dimension of this debate is centered around the impact of advanced technologies, e.g., robot adoption, on employment. On one hand, it is claimed that the demand for labor increase due to productivity effect.[1] On the other hand, there are evidences showing that advanced technologies can affect the employment, wages and skill polarization (See e.g., Acemoglu and Restrepo, 2020; Acemoglu et al., 2020; Michaels et al., 2014 ; Dauth et al., 2018) due to displacement effect. The

[1]See e.g., Acemoglu and Restrepo (2020) ; Acemoglu and Restrepo (2019).

increased adoption of advanced technologies has an impact on other outcomes such as productivity (e.g., Graetz and Michaels, 2018; Dauth et al., 2018). Despite the importance of the topic, there is a limited systematic evidence at the firm level. In this paper, we aim to fill this gap by providing firm level evidence on the impact of digital adoption from 27 EU countries.

In this paper, we mainly examine the impact of digital technology adoption on various firm outcomes by using a unique firm level survey from the European Investment Bank (EIB). As in previous studies, we do not limit our analysis to only adopting robots but consider many different technology adoptions, such as robotics, big data analytics and 3D printing.[2] Since the impact of adopting various technologies is more comprehensive than the impact of just robot adoption, we mostly focus on the firm outcomes such as labor productivity, TFP and wages. In addition to these outcomes, we also investigate the impact on the investment in innovation, firms' management and training practices with respect to digital technology adoption. We first show that size and productivity are important determinants of digital technology adoption. Then, we establish a causal relationship between digital technology adoption and outcomes at the firm level by developing instruments that combine input-output linkages between country-industry groups and sector specific digital patent stocks.

Since the adoption of digital technologies is not a random decision, it poses an endogeneity problem. We address this endogeneity concern by providing an instrument in the spirit of shift-share instruments.[3] Our identification strategy utilizes input-output linkages across country-industry groups and digital patent stocks to quantify the effect of digital adoption on firms' outcomes. Particularly, using pre-existing (initial) input-output linkages, we construct two different share components: upstream and downstream shares. The digital patent stocks (lagged) at the industry and year level in other industries are used as a shift component. Combining these shifts and share parts, we create two different (upstream and downstream) weighted digital patent stock measures at the country-sector-year level as a proxy for digital adoption of firms.

To implement our empirical strategy, we combine comprehensive firm level survey with patent data. First, we use the EIB Investment Survey (EIBIS) to observe the digital adoption decisions of firms. In this survey, digital adoption is observable for the years between 2018-2021. The survey also provides standard information at the firm level, such as sectoral information, employment and fixed asset levels. We complement this firm level survey with the Intellectual Property data of World Top R&D Investors from JRC to calculate

[2]The survey question includes different digital technologies. Details about the survey question are provided in Section 3.2.

[3]See e.g., Goldsmith-Pinkham et al. (2020) and Borusyak et al. (2022).

digital patent stocks at the industry-year level for the shift part of our instrument. We build our measure of digital innovation by classifying patents into digital and non-digital related categories.[4] Finally, we use input-output tables from Eurostat to construct upstream and downstream coefficients which constitute the share part of our instrument.

We present two main results. First of all, we show that bigger and productive firms are more likely to adopt digital technologies. Then, we claim that the upstream and downstream digital patent stocks at the industry-year level are legitimate proxies for the firms' digital adoption. Using 2SLS, our estimates suggest that digital technology uptake increases TFP and labor productivity more than %100.[5] We also find a significant increase in average wages after digital adoption. In addition, we observe that the digital uptake affects firms' training and management practice decisions positively. Finally, we observe a positive relationship between firms' digital uptake and investment in innovation.

We perform many different robustness checks. In particular, we investigate results by using alternative controls and share of weighted digital patents instead of using the level of digital patent stocks as instruments. We also replicate results by limiting the sample to manufacturing firms and to specific country groups. Our results are robust to all of these checks. In addition, our results are robust using difference-in-differences techniques with a propensity score matching and re-weighting in the spirit of Guadalupe et al. (2012) and Koch et al. (2021).

Related Literature Our paper contributes to the literature examining the impact of the adoption of advanced technologies. Some of these studies mainly focus on robot adoption. By investigating the impact of computerisation, Frey and Osborne (2017) provides one of the first evidence on the impact of computerisation on employment. They claim that a significant part of total employment in the US is at risk. Also, Dauth et al. (2018) examines the effects of robot adoption on employment, wages and composition of jobs. They observe a noticeable alteration in the composition of jobs along with an increase in the labor productivity and a decrease in the labor share. Acemoglu and Restrepo (2020) also shows that robot adoption decreases wages and employment to population ratio by a considerable amount. Another important paper by Graetz and Michaels (2018) links a substantial increase in labor productivity growth and wages to robot adoption. Acemoglu et al. (2020) suggest that the firms adopting robots in France experience an increase in value-added and productivity while reducing the labor share. Using a firm level dataset from Spain, Koch et al. (2021) show a positive effect of robot adoption on firms' output and negative effect on labor share. Instead of solely focusing on only robot adoption, a few papers also explore

[4] We use the classification from Inaba and Squicciarini (2017). See Section 3.2 for more details.

[5] In Section 3.6, we discuss our results.

the outcome of adopting advanced technologies from a broad perspective. For instance, Bessen and Meurer (2013) provide evidence from the Netherlands using firm level data and argue that automating firms experience faster employment and revenue growth than non-automating firms. In addition, Acemoglu et al. (2022) investigates the impact of the adoption of automation technologies by US firms across all economic sectors. They show that the adoption of these technologies mostly concentrates on large and young firms. They also claim that the adopters have higher labor productivity and lower labor shares. Dixon et al. (2021) links robot adoption to organizational structure. Brunello et al. (2023) also connects advance digital technology adoption to firms' employee training decisions with a control function approach.

Our paper, particularly the construction of our instrument, also relates to vast literature that links technology diffusion to economic growth and innovation.[6] A recent paper by Berkes et al. (2022) investigates the causal effect of innovation induced by international spillovers on value-added per worker and TFP at the sectoral level. Additionally, Ayerst et al. (2020) link diffusion of knowledge embedded in trade patterns to the patenting outcomes by utilizing input-output linkages and international patent data. Cai and Li (2019) also examines the network of knowledge linkages between sectors and its impact on firm innovation and aggregate growth.

Our paper differentiates from the papers investigating the impact of advanced technologies in two ways. First of all, we provide evidence by using unique firm level survey data from 27 EU countries. Second, existing papers using micro-level data mostly investigate the impact of robot adoption. We differentiate from these papers not only focusing on robot adoption but providing results on various other digital technology adoptions such as AI technologies, drones, 3D printing etc. In addition, we provide different firm level outcomes like investment in innovation or training. This paper also differentiates from the papers investigating the impact of international spillovers by particularly focusing on the impact of digital adoption. Our paper contributes to these various strands of the literature by first presenting the determinants of digital adoption at the firm level and then quantifying the impact of digital technology adoption using novel instruments.

The remainder of our paper is organised as follows. In Section 3.2 we describe the dataset and provide descriptive evidence. In Section 3.3 we analyse the determinants of digital technology adoption and in Section 3.4 we investigate the impact of digital adoption on firms' outcomes. In Section 3.5 we offer multiple robustness checks including difference-in-differences technique with a propensity score matching. Section 3.6 provides the discussion of findings. Section 3.7 concludes.

[6] See e.g., Acemoglu et al., 2016 ; Oberfield, 2018 ; Liu, 2019.

3.2 Data

3.2.1 Data Sources

Firm level survey We use EIBIS survey which covers 12 000 firms each year across the EU27 since 2015. It provides rich and very detailed information mostly about investment decisions and investment finance choices of firms. This data offers an unique advantage by providing information on whether firms adopted any digital technologies.

We exploit data across 4 years from 2018 to 2021. This the complete sample period which we can observe digital adoption of firms. In the first three waves the structure of the question slightly differs from the last wave. In particular, for the first three waves, question is stated as follows: 'Can you tell me for each of the following digital technologies if you have heard about them, not heard about them, implemented them in parts of your business, or whether your entire business is organised around them?'. While for the last wave, the question is re-framed and changed to the following structure: 'To what extent, if at all, are each of the following digital technologies used within your business? Please say if you do not use the technology within your business.' The definition of digital technologies differ from one sector to another slightly. If the firm operates in the Manufacturing sector the digital technologies include 3D printing , robotics, internet of things, big data analytics. Instead if firm operates in the service sector, the digital technologies include augmented or virtual reality, platform technologies, internet of things and big data analytics. Third, If firm operates in construction sector 3D printing, drones, augmented or virtual reality and internet of things. Finally, for the firms operates in the other sectors, the digital technologies include 3D printing, platform technologies, internet of things, big data analytics. Based on the responses, we create a binary indication variable which takes value of 1 if firm adopted digital technologies at the time t.

We can also observe/derive standard variables such as employment, value added, cost of employees and sector information for the years between 2018-2021. In addition, we can observe more detailed information on whether firms' investing in new product development and/or training. We also have information on whether they adopted new management practices. We deflate all the monetary values using Harmonised Indices of Consumer Prices (HICP) from Eurostat.

We use TFP and labor productivity as main outcomes. The total TFP is constructed by simply estimating sector specific regressions by using value-added, capital and labor levels of the firms using Cobb-Douglas formulation.[7] After estimating the labor and capital

[7] Since we do not observe any material costs, we can not apply advanced techniques such as Levinsohn and Petrin (2003) and Ackerberg (2015) to calculate TFP.

coefficients, TFP is constructed as simply calculating the residual.[8] Alternatively, we use value-added per worker as an labor productivity measure. In addition, we consider wage per worker and binary outcome variables as dependent variables. In particular, we consider firms' training and advance management practices (whether firms adopt strategic business monitoring system). Finally, we investigate how digital adoption affects firms' investment decision in innovation.[9] Before turning into analysis, we follow simple cleaning procedures. We first drop negative and zero values in standard variables. Then we drop top one and bottom one percentage of standard variables such as employment, fixed-assets and wages. We also get rid of firms show extraordinary increase or decreases (top one and bottom one percentage) in labor productivity and value-added.

Patent Data We supplement firm level data with the world Top R&D Investors Intellectual Property database from JRC. This database consist of many different dataset including standard firm information like industry or location. It also includes patent portfolio of firms along with the patent class information. In particular, patent data includes publication authority, year of filing and patent classes such as IPC and WIPO. We use this data to calculate the patent stocks for each country-industry-year group and create the shift part of our instrument. Since, ICT capabilities are crucial to the digitalization process (See e.g., Deloitte, 2013 ; OECD, 2020.), we use ICT patent classification from Inaba and Squicciarini (2017) and classify patents into digital vs non-digital categories using their IPC codes. Using yearly digital (ICT) related patent information, stock of patents is calculated by simply summing up the number of digital patents.

Input Output Tables Additionally, we use Input-Output Tables from Eurostat. In particular, we use the FIGARO tables which includes EU inter-country Supply, Use and Input-Output tables. We specifically use 2017 Input Output Tables to construct the share part of our instrument.[10] After calculating the upstream (downstream) shares we use patent stocks to construct the country-sector-year instruments.

3.2.2 Descriptive Analysis

Before turning to the estimation part, we present the simple statistics from our sample. Table 3.1 in below show the firm level standard measures by separating firms into digital adopters and non-digital adopters. Different patterns are observed between digital technology adopter firms and non-digital technology adopter firms. First of all, firms adopting digital technologies are, on average, larger and more productive. Second, they have, on av-

[8] Due to number of observations, for some sectors, the TFP can not be constructed.
[9] Unfortunately, we can not observe firm level skill composition.
[10] Construction of shares are explained in detail in the Section 3.4

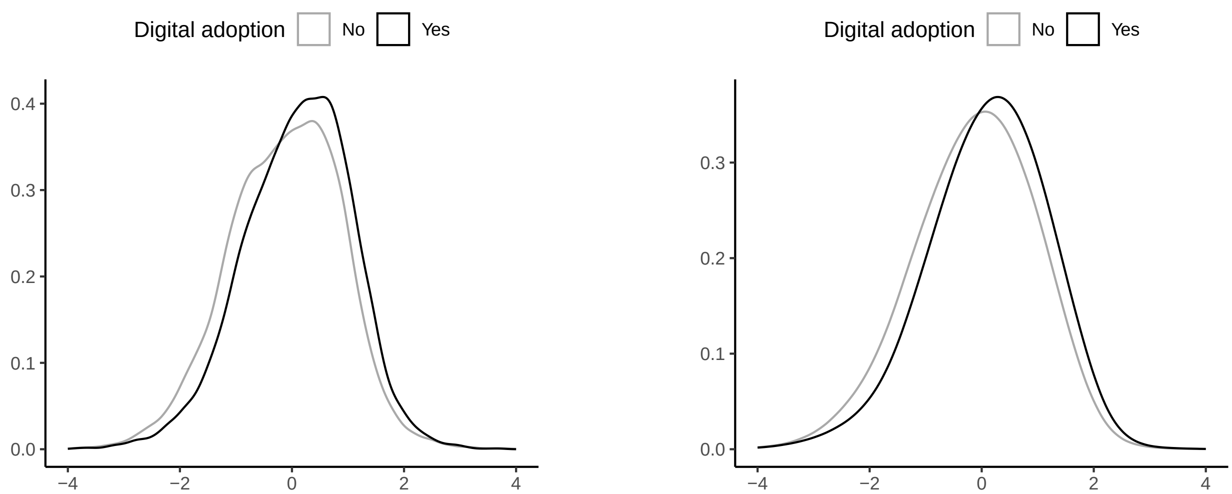
erage, higher wages per worker. Finally, digital adopters are more likely to be exporters and more likely to be investing in training and innovation.

Table 3.1: Summary Statistics

	N	Mean	St. Dev.	Median	Pctl(25)	Pctl(75)
				Digital Adopters		
Log(FixedAssets)	20,836	14.243	2.230	14.444	12.603	15.815
Log(Value-Added)	19,741	14.248	1.652	14.300	12.975	15.553
Log(Value-Added/Emp)	19,741	10.308	0.836	10.363	9.764	10.885
Log(TFP)	19,070	9.048	0.852	9.074	8.479	9.612
Employment	22,756	132.236	219.731	53	14	150
Log(Wage/Emp)	21,215	10.052	0.800	10.113	9.558	10.639
Exporter(Binary)	22,698	0.555	0.497	1	0	1
Age(Category)	22,754	3.485	0.800	4	3	4
Investment in Innovation(Binary)	19,521	0.474	0.499	0	0	1
Innovation Investment Share	19,521	0.189	0.288	0.000	0.000	0.300
Training Binary	20,276	0.561	0.496	1	0	1
Management Practices Uptake	22,235	0.567	0.495	1	0	1
Digital Patents(Downstream)	22,756	15,162.420	13,319.190	10,724.040	5,753.027	21,009.120
Digital Patents(Upstream)	22,756	6,204.222	5,879.814	4,773.565	2,467.383	7,682.188
				Non-Digital Adopters		
Log(FixedAssets)	17,539	13.332	2.147	13.291	11.798	15.019
Log(Value-Added)	16,372	13.467	1.536	13.342	12.361	14.529
Log(Value-Added/Emp)	16,372	10.115	0.869	10.160	9.532	10.727
Log(TFP)	15,596	8.886	0.852	8.915	8.316	9.474
Employment	19,885	70.633	145.609	20	9	70
Log(Wage/Emp)	18,125	9.858	0.826	9.911	9.339	10.469
Exporter(Binary)	19,818	0.382	0.486	0	0	1
Age(Category)	19,879	3.426	0.835	4	3	4
Investment in Innovation(Binary)	15,680	0.327	0.469	0	0	1
Innovation Investment Share	15,680	0.131	0.261	0.000	0.000	0.100
Training Binary	17,861	0.418	0.493	0	0	1
Management Practices Uptake	19,402	0.335	0.472	0	0	1
Digital Patents(Downstream)	19,885	12,787.330	12,495.260	8,174.711	4,336.243	16,986.070
Digital Patents(Upstream)	19,885	5,736.456	4,916.021	4,860.641	2,466.898	6,837.781

To provide graphical evidence on the relationship between digital technology adoption and firm size/productivity, we plot the distribution of value added and value added per worker for firms adopt digital technologies versus firms do not adopt digital technologies. Figure 3.1 presents the distribution of firms' value-added per worker and wage per worker for the digital technology adopters vs non-digital technology adopters. Both of the wage per worker and labor productivity distribution of firms adopting digital technologies dominate the non-adopter firms.

Figure 3.1: Distribution of Firms' Value-Added per Worker and Wage per Worker



Note. Panel (a) depicts the distribution of standardized log value-added per worker with digital technology separation. The black line presents the density of value-added per worker for digital technology adopters while gray line presents the density of value-added per worker for non-digital technology adopters. Panel (b) shows the same as panel (a) using standardized log wage per worker.

3.3 Determinants of Digital Technology Adoption

Before examining the impact of digital adoption on firms' outcome, in this section, we explore the determinants of digital technology adoption. In order to understand the direction of the selection, we formally analyse the determinants of the digital technology adoption.

To analyse the determinants of the digital technology adoption, we estimate the following equation.

$$DigitalAdoption_i = \boldsymbol{\psi F_{i0}} + \mu_c + \delta_s + \epsilon_i \tag{3.1}$$

where dependent variable is 0/1 indicator variable for digital technology adoption which takes value of 1 if firm i operating in sector s in country c ever adopts digital technologies during the sample period. $\mathbf{F_{i0}}$ denotes the vector of time-invariant (initial level, 0) firm level controls: log of labor productivity, total assets, average wage and innovation investment share. We also control firms' exporter status and firm age category. μ_c, and δ_s denotes country, and sector fixed effects (CPA1), respectively.

Table 3.2 presents OLS estimates of equation 3.1. Standard errors are clustered at the country-industry level as in Berkes et al. (2022). We found that in all of these specifications, the impact of labor productivity and firm size (log employment) is economically, statistically significant and positive. We also observe a positive correlation between wages and digital adoption. We also consider other specifications. In the Table C.1.1 in Appendix C.1, we also provide the results with probit model.

Table 3.2: Determinants of Digital Adoption

Dependent Variable:	Digital			
Model:	(1)	(2)	(3)	(4)
Variables				
ln(VA/Emp)	0.0700***	0.0626***	0.0506***	0.0381***
	(0.0056)	(0.0049)	(0.0079)	(0.0082)
ln(Emp)		0.0693***	0.0690***	0.0631***
		(0.0029)	(0.0029)	(0.0029)
ln(Wage/Emp)			0.0169**	0.0215***
			(0.0076)	(0.0082)
Exporter Status				0.0817***
				(0.0096)
Innovation investment share				0.1199***
				(0.0121)
Fixed-effects				
Sector	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes
Fit statistics				
Observations	23,777	23,777	23,777	20,354
R^2	0.07243	0.10707	0.10724	0.11610

Note. Column 4 includes also the age categories. Clustered (Country & Sector (CPA1)) standard-errors in parentheses. *p<0.1; **p<0.05; ***p<0.01. The last column also include age categories as control variable.

3.4 The Effects of Digital Technology Adoption

In this section, we aim to identify the impact of the digital adoption. Using instrumental variables strategy, we investigate the impact of the digital technology adoption mainly on the firms' productivity such as labor productivity and TFP. Additionally, we examine the effect on the average wages, training uptake, management practices, and innovation investment share.

Formally, we estimate the following equation. Y_{it} is one of the following variables: log labor productivity, log TFP, log average wage, training and management practices[11],innovation investment (binary and share) for firm i in country c operating in sector s (CPA categories) at time t.

$$Y_{it} = \alpha + \beta DigitalAdoption_{it} + \boldsymbol{\tau X_{it}} + \mu_c + \gamma_t + \delta_s + \epsilon_{it} \tag{3.2}$$

[11]In the survey, firms are asked whether they adopted strategic business monitoring system or not. If they adopted this variable takes value of 1, 0 otherwise.

where $DigitalAdoption_{it}$ refers to binary digital adoption variable which takes value of 1 if firm adopts digital technologies at time t. This variable is instrumented by using patent data and IO tables. $\mathbf{X_{it}}$ is a time varying vector of firm level controls including size, age and exporter categories. μ_c, γ_t and δ_s denotes country, year, sector fixed effects (CPA1), respectively.

The main coefficient of interest is β. It relates the changes in firms' digital adoption at the firm-year level to the to the changes in firms' outcomes such as productivity and average wages. We include sector, country and year fixed effects. Country and sector fixed effects allows us to control time invariant country and sectors specific patterns since firms in different countries and industries might have different propensity in terms of digital adoption. While year fixed effects control for year specific trends.

We first present the main impacts on TFP, labor productivity and average wage. The baseline results uses 27 EU countries for the period between 2018-2021. Before turning into investigating causal relationship, we examine the simple correlation between firms' digital adoption and outcomes. The detailed table of these estimations can be found in the Table 3.3. Results suggest that that the digital adoption is associated with more than %9 increase in labor productivity while this number is equal to %7 and %8 for TFP and average wage, respectively. Linear probability models in column (4), (5) and (6) suggest that the there is a positive correlation between firms' digital adoption and training decisions, management practices and investment in innovation.

Table 3.3: Digital Adoption and Firms' Outcome

Dependent Variables:	ln(VA/Emp)	ln(TFP)	ln(Wage/Emp)	Training	Mngmt Prac.	Innov.(Binary)	Innov.(Share)
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables							
Digital	0.0964***	0.0729***	0.0851***	0.1186***	0.1492***	0.1126***	0.0434***
	(0.0086)	(0.0087)	(0.0067)	(0.0058)	(0.0055)	(0.0066)	(0.0037)
Fixed-effects & Controls							
Wave	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics							
Observations	36,058	34,617	39,275	38,066	41,529	35,135	35,135
R^2	0.42706	0.44706	0.49115	0.12553	0.18814	0.08470	0.06615

Note. Clustered (Country & Sector (CPA1)) standard-errors in parentheses. *p<0.1; **p<0.05; ***p<0.01. Controls include exporter status, age and size categories.

To establish causal relationship between digital adoption and firms' outcome, we need to identify variation in digital adoption that is orthogonal to unobserved factors that might affect digital adoption and outcome variables at the same time. Due to reverse causality and attenuation bias, the direction of bias is ambiguous. To deal with these biases, our methodology depends on the instrumental variables strategy. To further explain the details of our strategy, in the first stage of the estimation, we consider following equation.

$$DigitalAdoption_{it} = \boldsymbol{\rho Z_{cst}} + \boldsymbol{\tau X_{it}} + \mu_c + \gamma_t + \delta_s + \epsilon_{it} \tag{3.3}$$

where $\mathbf{Z_{cst}}$ denotes instrumental variables: log of weighted upstream and downstream digital patents at the country-industry-year level.[12] As before, $\mathbf{X_{it}}$ is a time varying vector of firm level controls, operating in sector s in country c, including size, age and exporter categories.[13]

3.4.1 Instrument Construction

In this section, we present our identification strategy in detail. We build an instrumental variable for a digital patenting activity at the country-sector-year level to determine the digital adoption of firms. Our instrument uses both pre-existing country-sector linkages and digital patent stocks similar to shift-share design.[14] To construct the share terms of our instrument, we gather Input-Output table (2017) from Eurostat. We calculated upstream and downstream output-input coefficients as shares. In particular, for each country-sector of origin (c_o and s_o), we calculated the upstream and downstream shares using sector of destination, s_d. If the origin and destination sector equal to each other we equalize share to zero. Formally, the construction of measures are given by,

$$Upstream(Downstream)Share_{c_o,s_o,s_d} = \frac{M_{c_o,s_o,s_d}}{\sum_{s_d} M_{c_o,s_o,s_d}}$$

where M_{c_o,s_o,s_d} refers to the output levels. Sectors in the instrument construction part refers to the CPA categories. Alternatively, $\frac{M_{c_o,s_o,s_d}}{\sum_{s_d} M_{c_o,s_o,s_d}}$ the shares represent the input required to produce one unit of production of country-industry c_o and s_o from industry s_d.

Then, we used patent data from JRC. This data allow us to observe the patent stock of World Top R&D Investors. Using firms industry information at the NACE level, we first match their industries to the CPA categories. CPA stands for the statistical classification of products by activity (goods and services) at the level of the European Union. According

[12]For the sake of notation we use the same industry index for the instrument and fixed effects. While the instrument is at the IO table industry level (CPA), the sector fixed effects are at the higher level (CPA1) and covers all the CPA categories.

[13]We also consider alternative controls in Section 3.5.

[14]Our measure is constructed in the spirit of Berkes et al. (2022).

to CPA classification, each CPA product is assigned to one single NACE activity. Using this parallel structure, NACE classifications can be easily linked to CPA classifications. Then we merge firm information with the patent portfolios where we classify patents into digital vs non-digital categories using their IPC codes.[15] Then using yearly-digital patent information, stock of patents is calculated by simply summing up the number of digital patents. Finally, we multiply stock of patents with the corresponding shares we constructed above and add them to construct a weighted-digital patents at the country-industry of origin-year level instruments. Formally,

$$Z_{c_o,s_o,t} = \sum_{s_d} Upstream(Downstream)Share_{c_0,s_o,s_d} \times \overbrace{(\sum_{t=t_0}^{t-1} DigitalPatents_{s_d,t})}^{PatentStock_{s_d,t}}$$

where $Z_{c,s,t}$ is the log of weighted digital patents (upstream and downstream separately) and where $DigitalPatents_{s_d,t}$ is stock of digital at the CPA categories and time t for each country. Since all of the upstream and downstream weighted patent measures are above zero, we can use the log of them without any transformation. Our instrument predicts digital adoption in the current period based on pre-existing (initial) input-output linkages across countries and industries and digital patenting activity at the sector-year level. Instead of considering log stock of weighted-digital patents, we also consider share of weighted digital patents as instruments.[16] Our results are robust using this share of weighted patent measures. These results are presented in the Section 3.5.

3.4.2 Baseline Results

The results of the baseline estimation is depicted in the Table 3.4. The first three column present results for the TPF, labor productivity and average wages without the controls, while the last three column controls for age, size and exporter categories.[17] The magnitude of the two-stage least squares regressions is stable to adding controls.[18] In all of the specifications, we observe positive and significant effects of digital technology adoption on firms' productivity. The coefficients in columns (4), (5) and (6) suggest that digital adoption increases labor productivity, TFP and average wage of firms' by more than %100.[19]

[15]We use the classification from Inaba and Squicciarini (2017). See Section 3.2 for more details.

[16]In particular, we consider the share of weighted-digital patents in total weighted-digital patents in a sector instead of considering level of weighted-digital patents.

[17]Interestingly, there is no impact of digital technology adoption on firm output.

[18]We also consider additional control variables and lag control variables. These results can be found in Section 3.5.

[19]We discuss these results in the 3.6 comparing with the alternative methods.

Table 3.4: Effect of Digital Adoption on Firms' Outcome: Instrumental Variable

Dependent Variables:	ln(VA/Emp)	ln(TFP)	ln(Wage/Emp)	ln(VA/Emp)	ln(TFP)	ln(Wage/Emp)
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Digital	1.619***	1.829***	1.707***	1.487***	1.718***	1.698***
	(0.4195)	(0.4408)	(0.3476)	(0.4105)	(0.4166)	(0.3509)
Fixed-effects& Controls						
Wave	Yes	Yes	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	Yes	Yes	Yes
Fit statistics						
Observations	36,113	34,666	39,340	36,058	34,617	39,275
			First-Stage Estimates			
Ln(Upstream(Digital) Patents)	0.0224***	0.0235***	0.0216***	0.0236***	0.0247***	0.0231***
	(0.0074)	(0.0075)	(0.0074)	(0.0067)	(0.0068)	(0.0067)
Ln(Downstream(Digital) Patents)	0.0250***	0.0241***	0.0264***	0.0218***	0.0212***	0.0231***
	(0.0072)	(0.0072)	(0.0073)	(0.0070)	(0.0070)	(0.0070)
R^2 (1st stage)	0.06491	0.06568	0.06586	0.10878	0.10768	0.11206
F-test (1st stage)	40.931	39.239	46.009	38.423	37.388	43.578

Note. Clustered (Country & Sector (CPA1)) standard-errors in parentheses. *p<0.1; **p<0.05; ***p<0.01. Firm controls include exporter status, size and age categories. Same controls are used in the first stage. Kleibergen-Paap Wald F-stat is reported for the first stage.

In line with the literature, we claim that the average wage in firms adopting digital technologies increases since digital adoption might have implication on the skill composition of workers. In particular, if firms hire more skilled-workers after adopting digital technologies we expect to observe an increase in the average wage.[20] First stage coefficients and Kleibergen-Paap Wald F statistics are reported under the Table 3.4 which rules out the weak instrument concerns. We found a positive impact of our instrument on firms' digital technology adoption. In particular, we observe that %10 increase in the weighted upstream patents increases the digital adoption by around 0.2 percentage points across many specifications. While this number is slightly lower for the weighted upstream patents.[21] The estimated 2SLS coefficients are larger than OLS coefficients. This results might suggest that the OLS estimates suffer from attenuation bias. Alternatively, rising market concentration of market leaders might explain the downward bias in the OLS estimates.[22]

Impact on alternative outcomes We turn to the impact on firms adopting digital technologies on firms' training uptake and management practices. Due to adopting digital technologies, it might be expected to observe a change in the training and management

[20]Unfortunately, we can not observe the employment levels depending on skill composition.

[21]We also use downstream and upstream weighted patents separately in the first stage. The results are robust to this specification.

[22]See e.g., Akcigit and Ates (2021).

practices after digital technology adoption. If firms consider training as a complement to the digital technology adoption, we expect to observe a positive relationship. In addition, adoption of digital technologies might alter the management practices.[23] Table 3.5 presents these results. First two column present the results without the control variables while the last two column shows the results with the control variables. Results suggest digital adoption increases the probability of investing in training and adopting new management practices by almost 68 and 24 percentage points, respectively. Since we use binary indicator as a dependent variable, we also consider probit estimation with instrumental variable strategy. Results of these estimations can be found in the Table C.1.2 in Appendix C.1.

Table 3.5: Effect of Digital Adoption on Firms' Training and Management Practices

Dependent Variables:	Training	Mngmt Prac.	Training	Mngmt Prac.
Model:	(1)	(2)	(3)	(4)
Variables				
Digital	0.6659***	0.2212	0.6798***	0.2406*
	(0.1528)	(0.1486)	(0.1614)	(0.1404)
Fixed-effects & Controls				
Wave	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes
Fit statistics				
Observations	38,137	41,637	38,066	41,529
	First-Stage Estimates			
Ln(Upstream(Digital)Patent)	0.0284***	0.0237***	0.0292***	0.0249***
	(0.0077)	(0.0075)	(0.0070)	(0.0069)
Ln(Downstream(Digital)Patent)	0.0286***	0.0270***	0.0253***	0.0238***
	(0.0073)	(0.0070)	(0.0071)	(0.0067)
R^2 (1st stage)	0.06573	0.06609	0.11299	0.11251
F-test (1st stage)	60.525	52.997	57.272	50.177

Note. Clustered (Country & Sector (CPA1)) standard-errors in parentheses. *p<0.1; **p<0.05; ***p<0.01. Firm controls include exporter status, size and age categories. Same controls are used in the first stage. Kleibergen-Paap Wald F-stat is reported for the first stage.

Finally, we turn to the impact of digital adoption on firms' innovation decisions. We consider both binary and continuous measures of innovation uptakes: whether there is a positive investment in innovation and share of innovation investment to total investment. Table 3.6 presents the results of these estimations. As before the first two column present the results without the controls and the last column shows the estimations with control variables. As expected we observe an increase in the share of innovation investment. Digital adoption increases the probability of investing in innovation by almost 45 percentage

[23]See e.g., Dixon et al., 2021; Brunello et al., 2023.

points and increases share of innovation investment by 0.37.

Table 3.6: Effect of Digital Adoption on Firms' Innovation

Dependent Variables:	Innov.(Binary)	Innov.(Share)	Innov.(Binary)	Innov.(Share)
Model:	(1)	(2)	(3)	(4)
Variables				
Digital	0.5174***	0.4115***	0.4563***	0.3692***
	(0.1523)	(0.0981)	(0.1531)	(0.0918)
Fixed-effects& Controls				
Wave	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes
Fit statistics				
Observations	35,201	35,201	35,135	35,135
	First-Stage Estimates			
Ln(Upstream(Digital)Patent)	0.0183**	0.0183**	0.0200***	0.0200***
	(0.0076)	(0.0076)	(0.0071)	(0.0071)
Ln(Downstream(Digital)Patent)	0.0314***	0.0314***	0.0283***	0.0283***
	(0.0075)	(0.0075)	(0.0072)	(0.0072)
R^2 (1st stage)	0.06848	0.06848	0.11101	0.11101
F-test (1st stage)	47.504	47.504	45.151	45.151

Note. Clustered (Country & Sector (CPA1)) standard-errors in parentheses. *p<0.1; **p<0.05; ***p<0.01. Firm controls include exporter status, size and age categories. Same controls are used in the first stage. Kleibergen-Paap Wald F-stat is reported for the first stage.

3.5 Robustness Check

In this section, we present the results of the different robustness checks. We first show that our estimates are robust to using lag control variables and rest of the patent stocks. Then we show results where we replace the log weighted digital patent levels with the share of weighted digital patents. Finally, we limit our sample to only manufacturing firms. Our results are robust to all of these specifications. We also perform alternative robustness checks. The results of these robustness checks can be found in the Appendix C.1.

Alternative Controls As a first robustness check, we use lag control variables such as lag of log capital intensity (capital/employment), lag log employment in addition to exporter status and age categories. First three column of Table 3.7 presents these results. We also consider non-digital weighted patent stocks as control variable in addition to exporter status, age and size categories. The last three reports of Table 3.7 presents these results. Our results robust to all of these specifications.

Table 3.7: Effect of Digital Adoption on Firms' Outcome: Alternative Controls

Model:	Lag controls			Alternative controls		
Dependent Variables:	ln(VA/Emp) (1)	ln(TFP) (2)	ln(Wage/Emp) (3)	ln(VA/Emp) (4)	ln(TFP) (5)	ln(Wage/Emp) (6)
Variables						
Digital	0.8853**	0.9457**	1.136***	1.917**	2.396***	2.274***
	(0.3471)	(0.3681)	(0.2877)	(0.7909)	(0.8693)	(0.7207)
Fixed-effects& Controls						
Wave	Yes	Yes	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	16,004	15,625	17,029	36,058	34,617	39,275
	First-Stage Estimates					
Ln(Upstream(Digital)Patent)	0.0275***	0.0287***	0.0258***	0.0350***	0.0359***	0.0331***
	(0.0093)	(0.0093)	(0.0093)	(0.0118)	(0.0119)	(0.0117)
Ln(Downstream(Digital)Patent)	0.0309***	0.0297***	0.0330***	0.0019	0.0023	0.0061
	(0.0079)	(0.0079)	(0.0080)	(0.0161)	(0.0165)	(0.0156)
R^2	0.11875	0.11856	0.12103	0.10892	0.10781	0.11216
F-test (1st stage)	29.504	28.529	32.447	9.3570	9.5035	9.8876

Note. Clustered (Country & Sector (CPA1)) standard-errors in parentheses. *p<0.1; **p<0.05; ***p<0.01. First three column includes the lag employment, lag capital intensity, exporter status and age categories. The last three column uses add the log of non-digital upstream and downstream weighted patents as controls along with exporter status, age and size categories. Same controls are used in the first stage. Kleibergen-Paap Wald F-stat is reported for the first stage.

We also consider other outcome variables with alternative controls. These results can be found in the Table C.1.3 and Table C.1.4 in the Appendix C.1.

Manufacturing firms and alternative instruments We also consider alternative instruments. Instead of focusing on levels of digital patents, we use share of weighted digital patents in total patents. First three columns of Table 3.8 presents the results of an estimation when sample is restricted to only manufacturing firms. Alternatively, we use share of weighted digital patent stocks instead of the log of the weighted digital patent stocks. These results are given in the last three column of Table 3.8. The baseline results are robust across all of these specifications.

We also consider other outcome variables by using only manufacturing firms and alternative instruments. All of the outcome variables are robust to these specifications. These results can be found in the Table C.1.5 and Table C.1.6 in the Appendix C.1.

Alternative Classification and Country Groups We also consider alternative digital patent classification and we check the impact of digital adoption for different country groups. These results can be found in Table C.1.7, Table C.1.8, Table C.1.9, Table C.1.10 and Table C.1.11. Instead of considering both upstream and downstream digital patent stocks as instruments, we use them as separate instruments. Table C.1.12, Table C.1.13 and Table C.1.14 shows these results. Finally, we exclude top and bottom one percent of

Table 3.8: Effect of Digital Adoption on Firms' Outcome: Manufacturing Firms and Alternative Instruments

Model:	Manufacturing Firms			Alternative Instruments		
Dependent Variables:	ln(VA/Emp)	ln(TFP)	ln(Wage/Emp)	ln(VA/Emp)	ln(TFP)	ln(Wage/Emp)
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Digital	1.048***	1.281***	1.268***	1.727*	2.344**	2.121***
	(0.2728)	(0.2702)	(0.2140)	(0.8789)	(1.021)	(0.8010)
Fixed-effects& Controls						
Wave	Yes	Yes	Yes	Yes	Yes	Yes
Sector				Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	11,363	10,973	12,278	36,058	34,617	39,275
First-Stage Estimates						
Ln(Upstream(Digital)Patent)	0.0175**	0.0186**	0.0170**			
	(0.0079)	(0.0084)	(0.0081)			
Ln(Downstream(Digital)Patent)	0.0426***	0.0414***	0.0442***			
	(0.0097)	(0.0095)	(0.0098)			
Share (Upstream)				0.1119**	0.1145**	0.1021*
				(0.0546)	(0.0555)	(0.0531)
Share (Downstream)				0.0373	0.0389	0.0564
				(0.0704)	(0.0723)	(0.0687)
R^2 (1st stage)	0.12220	0.11911	0.12728	0.10718	0.10607	0.11038
F-test (1st stage)	54.027	50.977	61.384	6.0956	6.1771	6.5799

Note. Clustered (Country & Sector (CPA1)) standard-errors in parentheses. *p<0.1; **p<0.05; ***p<0.01. Controls include exporter status, age and size categories. Same controls are used in the first stage. Kleibergen-Paap Wald F-stat is reported for the first stage.

continuous dependent variables. Results are presented in Table C.1.15.

Propensity Score Matching (PSM) We also investigate the causal relationship between digital technology adoption and firm outcomes, with propensity score matching and propensity score re-weighting similar to Koch et al. (2021) and Guadalupe et al. (2012). We use propensity score matching to construct similar distribution of key variables across digital adopters and non-adopters. Similar to Koch et al. (2021), propensity scores are estimated by sorting firms that adopt digital technologies in particular year into the treatment group and those that never adopt digital technologies into the control group. We run probit regressions for digital technology adoption on one year lag of log total assets, log labor productivity growth and log value-added growth, age categories, sector, country and exporter dummies. We also consider year dummies and one year lag of innovation investment share in total yearly investment.[24] After extracting weights from the propensity score matching, we estimate the impact of digital adoption on firms' outcome. Table 3.9 presents these results. First two column presents the results for TFP and labor productivity. Third column shows the results for the wage per worker while last three columns present results for the firms' training and management practices adoption along with firms' innovation investment decisions.[25]

[24] We do not consider any other main dependent variables as a control variables in the matching.

[25] Note that using the lag of variables for the matching reduces the number of observations substantially

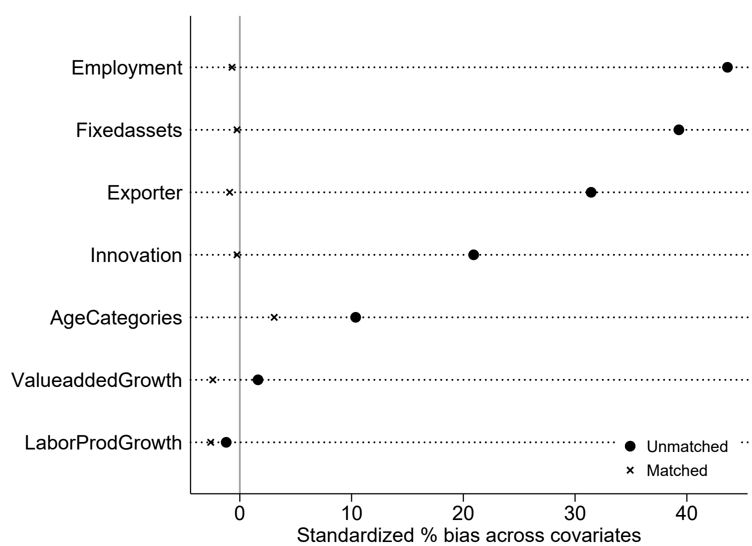
Table 3.9: Effect of Digital Adoption on Firms' Outcome: PSM

Dependent Variables:	ln(VA/Emp)	ln(TFP)	ln(Wage/Emp)	Training	Mngmt Prac.	Innov.(Binary)	Innov.(Share)
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables							
Digital	0.058***	0.047***	0.045***	0.244***	0.383***	0.316***	0.048***
	(0.014)	(0.013)	(0.014)	(0.033)	(0.032)	(0.038)	(0.008)
Fixed-effects & Controls							
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	No	No	No	No
Fit statistics							
Observations	11,213	11,213	10,843	10,675	11,055	10,266	10,268
R-squared	0.484	0.581	0.601				0.055
Pseudo R2				0.0913	0.0933	0.0584	

Note. Clustered (Country & Sector) standard-errors in parentheses. *p<0.1; **p<0.05; ***p<0.01. Column 4, 5 and 6 reports probit estimates while the other columns report OLS estimates.

Results suggest that the digital adoption increases the labor productivity, TFP and average wage around 6% to 4%. Figure 3.2 provide visual representation of the reduced deviation between treated and control groups. We also provide evidence on the balancing of variables respect to digital uptake by simply investigating the impact of digital uptake on the variables used for matching. These can be found in Table C.1.17 in Appendix C.1.

Figure 3.2: Reduction of bias after matching



and to compare baseline effects without the matching techniques to the results with matching techniques, in this part, we consider firms where the variables used for matching is observed. These results, without the propensity score matching, propensity score reweighting and entropy balancing, are the presented in Table C.1.16 in Appendix C.1.

Figure C.1.1 in Appendix C.1 also provides the propensity score distributions before and after matching. We observe that after matching the propensity scores distributes similarly across treated and control groups.

We also consider propensity score re-weighting and entropy balancing.[26] As in PSM, we consider the same variables to calculate the the weights in both of propensity score re-weighting and entropy balancing. The results of these regressions are presented in Table 3.10 and Table 3.11.[27]

Table 3.10: Effect of Digital Adoption on Firms' Outcome: PS Reweighting

Dependent Variables:	ln(VA/Emp)	ln(TFP)	ln(Wage/Emp)	Training	Mngmt Prac.	Innov.(Binary)	Innov.(Share)
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables							
Digital	0.047***	0.042***	0.043***	0.269***	0.383***	0.334***	0.050***
	(0.014)	(0.012)	(0.013)	(0.035)	(0.029)	(0.032)	(0.006)
Fixed-effects & Controls							
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	No	No	No	No
Fit statistics							
Observations	11,943	11,943	11,529	11,380	11,779	10,909	10,912
R^2	0.496	0.594	0.598				0.046
Pseudo R2				0.100	0.0947	0.0507	

Note. Clustered (Country & Sector) standard-errors in parentheses. *p<0.1; **p<0.05; ***p<0.01. Column 4, 5 and 6 reports probit estimates while the other columns report OLS estimates.

Table 3.11: Effect of Digital Adoption on Firms' Outcome: Entrophy Balancing

Dependent Variables:	ln(VA/Emp)	ln(TFP)	ln(Wage/Emp)	Training	Mngmt Prac.	Innov.(Binary)	Innov.(Share)
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables							
Digital	0.063***	0.054***	0.049***	0.265***	0.365***	0.315***	0.050***
	(0.012)	(0.011)	(0.012)	(0.032)	(0.030)	(0.034)	(0.007)
Fixed-effects & Controls							
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	No	No	No	No
Fit statistics							
Observations	11,957	11,957	11,532	11,389	11,786	10,922	10,926
R^2	0.482	0.578	0.601				0.057
Pseudo R2				0.0920	0.0944	0.0555	

Note. Clustered (Country & Sector) standard-errors in parentheses. *p<0.1; **p<0.05; ***p<0.01. Column 4, 5 and 6 reports probit estimates while the other columns report OLS estimates.

[26] For propensity score re-weighting, we only keep those observations in the analysis that are in the region of common support.

[27] All observed characteristics used for the weighting of digital adopters and non-adopters are balanced and these results are available upon request.

3.6 Discussion of Findings

In this section, we provide a discussion of our findings. First, compared the baseline results without the instrumental variables strategy, we argue that the results obtained using the instrumental variable suggest a substantial impact of digital adoption on firms' labor productivity, TFP, and wages. Although the samples, estimations and the outcome variables differ, our results indicate much larger effects on various firm-level outcomes, deviating from important papers in the literature.[28]

Furthermore, it is important to note that the impact of digital adoption, as assessed through the PSM, propensity score reweighing, and entropy balancing methodologies, suggests an alternative direction for the bias compared to the results obtained using the instrumental variable.

We are aware that these evidences may cast doubt on our baseline findings using the instrumental variable, and as a result, we aim to conduct further analyses to better understand these observed deviations and contrasting directions in the biases. In future, we also intend to enhance our instrument by utilizing patent citation indexes from PATSTAT instead of relying solely on input-output tables.

3.7 Conclusion

This paper provides novel evidence on the impact of digital adoption on firm level outcomes. By using unique firm level data from 27 EU countries, we first show that big and more productive firms are more likely to adopt digital technologies. Then we construct novel instruments by leveraging pre-existing input-output linkages across countries-industry groups and digital patent stocks at industry-year levels. Our 2SLS estimates suggest that the digital adoption leads to significant increases in TFP, labor productivity and wages. Additionally, we observe that the firms' training, management practices and investment in innovation are positively impacted by digital adoption.

We show that our results are robust to many alternative specifications and robustness checks. We first show that our results are not affected by the control variables. Then we find that our results are robust using alternative instruments. Additionally, we provide evidence suggesting that our results are not driven by particular industry groups such as manufacturing. In addition, we consider difference-in-difference technique with propensity score matching and alternative methods. We observe a positive causal impact of digital adoption on firms' outcomes. Finally, we also provide a discussion of findings to argue the

[28]See Acemoglu et al., 2020; Koch et al., 2021; Graetz and Michaels, 2018.

potential drawbacks of the results.

Our findings, which focus on broader concepts of advanced technologies, provide novel evidence on how digital adoption can affect firm outcomes. Our results indicate that digital adoption has a significant impact on firm outcomes. Our findings, and more specifically our instruments, highlight an important determinant of digital uptake at the firm level: the importance of the innovation stock in upstream and downstream industries. Policies aimed at increasing firm productivity and controlling the employment effects of digital technology adoption should consider the impact of upstream and downstream partners as well as the firm itself.

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Appendix A

Appendix to Chapter 1

A.1 Figures and Tables

Table A.1.1: Anti-Patent Trolling Law Signed Year

State	Year of Enactment	State	Year of Enactment
Alabama	2014	Montana	2015
Alaska		Nebraska	
Arizona	2016	Nevada	
Arkansas		New Hampshire	2014
California		New Jersey	
Colorado	2015	New Mexico	
Connecticut		New York	
Delaware		North Carolina	2014
District of Columbia		North Dakota	2015
Florida	2015	Ohio	
Georgia	2014	Oklahoma	2014
Hawaii		Oregon	2014
Idaho	2014	Pennsylvania	
Illinois	2014	Rhode Island	2016
Indiana	2015	South Carolina	2016
Iowa		South Dakota	2014
Kansas	2015	Tennessee	2014
Kentucky		Texas	2015
Louisiana	2014	Utah	2014
Maine	2014	Vermont	2013
Maryland	2014	Virginia	2014
Massachusetts		Washington	2015
Michigan	2017	West Virginia	
Minnesota	2016	Wisconsin	2014
Mississippi	2015	Wyoming	2016
Missouri	2014		

Figure A.1.1: Demand Letter Example

BanIsh Law

John A. Lee
Banie & Ishimoto LLP
3705 Haven Ave. #137
Menlo Park, CA 94025
Phone: 650-241-2774
Email: jlee@banishlaw.com

VIA U.S. MAIL

April 10, 2017

Mr. Richard Schneider
Antennas Direct.com
16388 Westwoods Business Park
Ellisville, MO 63021

Re: Infringement of Landmark Technology, LLC's Patent Rights

Dear Mr. Schneider:

In February, Landmark offered a non-exclusive license to its patent portfolio for $45,000. Two months have elapsed and Antennas Direct.com has not responded to Landmark.

The current amount for a non-exclusive license to Landmark's patent portfolio license is $55,000 and the offer expires May 31, 2017.

Very truly yours,

John A. Lee
Partner
BANIE & ISHIMOTO LLP

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A.2 Comparative Statistics

Firm's objective is to maximize the expected lifetime sum of all discounted dividends where discount factor is normalized to 1 for simplicity. Firm chooses k_1,k_2, b_1,b_2 and c_1

subject to borrowing constraints and non-negativity constraints for the dividends, e.g., $d_0 \geq 0$,$d_1 \geq 0$ and $d_2 \geq 0$.

$$\max_{k_1,k_2,b_1,b_2,c_1} \quad [g(k_1) - k_1 + \pi(k_2) - k_2 + rc_1 - p(c_1)F]$$

$$\begin{aligned} b_1 &\leq \theta k_1 \\ b_2 &\leq \theta k_2 \\ c_0 + b_1 - k_1 - c_1 &\geq 0 \\ c_1(1+r) + b_2 - k_2 - p(c_1)F &\geq 0 \\ g(k_1) + \pi(k_2) - b_1 - b_2 &\geq 0 \end{aligned}$$

The firm is financially unconstrained if it has enough financing capacity to finance the first best investments, which are determined by FOCs. If the firm is financially constrained then its investment levels are lower than the first-best levels because of borrowing constraints. For the constrained firm, forgoing a dividend payment in period 0 and period 1 is a zero NPV and borrowing an additional dollar is also a zero NPV project. Therefore, it is optimal for the constrained firm not to pay any dividends in period 0 and period 1 and to exhaust its borrowing capacity. Using these conditions, capital levels are constructed as follows: $k_1 = \frac{c_0 - c_1}{1-\theta}$ and $k_2 = \frac{c_1(1+r)-p(c)F}{1-\theta}$. Using these conditions, when a solution is interior, the optimal cash holdings c_1^* satisfy the following first-order condition:

$$\pi'(\frac{(1+r)c_1^* - p(c_1^*)F}{1-\theta})(1 + r - p'(c_1^*)F) + \theta p'(c_1^*)F = g'(\frac{c_0 - c_1^*}{1-\theta}) + r\theta$$

In order to perform comparative statistics, I simply assume that the production functions are quadratic (e.g.,$\pi_{k_2} = k_2^2$) and the $p(c) = c\gamma$ is linear in cash holding. In this case, the optimal cash holding can be expressed as followed:

$$c_1^* = \frac{\theta(1-\theta)(r - \gamma F) + 2c_0}{2((1 + r - \gamma F)^2 + 1)}$$

The impact of γ on cash holding:

$$\frac{\partial c_1^*}{\partial \gamma} = \frac{F((1-\theta)\theta(\tau^2 - 2\tau - 1) + 4\tau c_0)}{2(\tau^2 + 1)^2}$$

where $\tau = 1 + r - \gamma F$. Simple comparative statistics shows that when F satisfies the following condition, the cash holding increases as γ decreases (State-laws).

$$\frac{2c_0\gamma - \gamma r\theta^2 + \gamma r\theta - \psi}{\gamma^2(1-\theta)\theta} < F < \frac{2c_0\gamma - \gamma r\theta^2 + \gamma r\theta + \psi}{\gamma^2(1-\theta)\theta}$$

where $\psi = \sqrt{2\gamma^2(2c_0^2 + 2c_0(\theta-1)\theta + (\theta-1)^2\theta^2)}$.

A.3 Variable Definition

The detailed explanation of variables are presented below.
Cash to Assets: Cash and marketable securities divided by book assets.
Cash to Net Assets: Cash and marketable securities divided by book assets minus cash and marketable securities.
N. Leverage (Net Leverage): Long-term debt plus debt in current liabilities minus cash and marketable securities to book assets.
Leverage: Long-term debt plus debt in current liabilities to book assets.
Cash flow volatility: Standard deviation of cash flow to book assets. This variable is constructed using data over the previous ten years for each firm and then averaged to the industry(SIC2) and year level.
Market to book ratio: Book value of assets-book value of equity+the market value of equity divided by the book value of assets.
Cash flow: Earnings after interest, dividends, and taxes before depreciation divided by book assets.
Capital expenditures: Capital expenditures divided by book assets.
Dividend paying status: Equal to one in years in which a firm pays a dividend (zero otherwise).
Acquisitions (Acq.) :Acquisitions divided by book assets.
R&D (Binary): Takes value of 1 if firm reports any positive R&D expenditure, 0 otherwise.
Herfindhahl-Hirshmann index (HHI): Sum of square of the market share of each firm competing in a industry. Calculated for each SIC4-year group.
Whited and Wu Index (WW-Index): -0.091*CashFlow -0.062*Dividend +0.021*Leverage -0.044*Size(Assets)+0.102*Industry Growth -0.035*Industry Growth(SIC4-year level sales growth).
Asset liquidation : 0.715*Receivables+0.547*Inventory+0.535*Property, Plant and Equipment(Net).

External Finance Dependence (**Exfin**): Capital expenditures-Cash divided by Capital expenditures.

A.4 Additional Empirical Analyses

Table A.4.1: Effect of Baseline Variables on Treatment Status

	Treatment			
Model:	(1)	(2)	(3)	(4)
Variables				
Cash/Asset	−0.015		−0.016	
	(0.017)		(0.026)	
N.Leverage		0.017		0.020
		(0.014)		(0.016)
Employment	−0.012	−0.013		
	(0.019)	(0.019)		
Assets			−0.020	−0.021
			(0.014)	(0.014)
Acq.	−0.008	−0.008	−0.008	−0.008
	(0.012)	(0.012)	(0.014)	(0.014)
Dividend Status	−0.023	−0.022	−0.021	−0.020
	(0.020)	(0.020)	(0.024)	(0.025)
CashFlow	−0.016	−0.015	−0.016	−0.015
	(0.012)	(0.012)	(0.013)	(0.013)
MTB	0.007	0.006	0.007	0.006
	(0.013)	(0.013)	(0.014)	(0.014)
Capital Exp.	0.021	0.022	0.020	0.021
	(0.017)	(0.017)	(0.019)	(0.019)
R&D Stock	0.003	0.003	0.001	0.001
	(0.010)	(0.010)	(0.010)	(0.010)
Fit statistics				
Observations	1,486	1,486	1,486	1,486
R^2	0.303	0.303	0.304	0.304

Note. All the baseline characteristics from the year 2010. Column 1 and column 2 shows the results using employment as firm size while column 3 and column 4 presents results with total assets to control firm size. All variables are standardized. Results are also robust using non-standardized version of the baseline variables.

Table A.4.2: Effect of the Anti-patent Trolling Laws on the Cash & Net Leverage: R&D Stock Status

	Innovative			non-Innovative		
	Cash/Asset	Cash/N.Asset	N.Leverage	Cash/Asset	Cash/N.Asset	N.Leverage
	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
PostEvent	0.0166**	0.1568**	-0.0582***	0.0014	0.0006	0.0148
	(0.0067)	(0.0678)	(0.0146)	(0.0045)	(0.0119)	(0.0092)
Fixed-effects & Controls						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	8,870	8,870	8,870	6,233	6,233	6,233
R^2	0.87102	0.74127	0.80741	0.83874	0.83012	0.84810
Mean	0.2646	0.7273	-0.0560	0.1234	0.2288	0.1734

Note. Clustered (State) standard-errors in parentheses. *p<0.1; **p<0.05; ***p<0.01. Firm controls include cash flow, capital expenditure, acquisitions, R&D report dummy, market to book ratio, log employment, dividend paying status in any given year and industry cash flow volatility.

Table A.4.3: Effect of the Anti-patent Trolling Laws on the Cash & Net Leverage: Patent Stock Status

	Patent Owner			non-Patent Owner		
	Cash/Asset	Cash/N.Asset	N.Leverage	Cash/Asset	Cash/N.Asset	N.Leverage
	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
PostEvent	0.0142**	0.1620**	-0.0525***	0.0086	0.0574	0.0034
	(0.0063)	(0.0642)	(0.0143)	(0.0071)	(0.0386)	(0.0101)
Fixed-effects & Controls						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	6,736	6,736	6,736	8,367	8,367	8,367
R^2	0.87240	0.74022	0.79934	0.85789	0.77811	0.80091
Mean	0.2637	0.7187	-0.0593	0.1602	0.3628	0.1175

Note. Clustered (State) standard-errors in parentheses. *p<0.1; **p<0.05; ***p<0.01. Firm controls include cash flow, capital expenditure, acquisitions, R&D report dummy, market to book ratio, log employment, dividend paying status in any given year and industry cash flow volatility.

Table A.4.4: Effect of the Anti-patent Trolling Laws on the Cash & Net Leverage: R&D Interaction

Model:	Cash/Asset (1)	Cash/N.Asset (2)	N.Leverage (3)	Cash/Asset (4)	Cash/N.Asset (5)	N.Leverage (6)
Variables						
PostEvent	0.0011	0.0309	0.0002	0.0004	0.0231	-0.0079
	(0.0042)	(0.0195)	(0.0090)	(0.0041)	(0.0216)	(0.0087)
PostEvent × R&D Stock Status	0.0096*	0.0856**	-0.0400***			
	(0.0056)	(0.0340)	(0.0121)			
R&D				-0.0067	-0.0805	-0.0054
				(0.0112)	(0.0851)	(0.0254)
PostEvent × R&D				0.0124**	0.1135***	-0.0299**
				(0.0058)	(0.0384)	(0.0127)
Fixed-effects						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	15,103	15,103	15,103	15,103	15,103	15,103
R^2	0.87961	0.76322	0.84286	0.87963	0.76329	0.84279
Mean	0.2063	0.5216	0.0386	0.2063	0.5216	0.0386

Note. Clustered (State) standard-errors in parentheses. *p<0.1; **p<0.05; ***p<0.01. The first three column interact the PostEvent indicator with the R&D Stock Status (as explained in Section 1.4) before the initial state-law. While the last three column uses yearly-firm level R&D status. Firm controls include cash flow, capital expenditure, acquisitions, market to book ratio, log employment, dividend paying status in any given year and industry cash flow volatility.

A.5 Additional Evidence on the Probability of Being Targeted by PAEs

In this section, I merge my sample with the Stanford Litigation Database (Miller, 2018) to observe firm-year level litigation cases brought by PAEs. In line with the classification suggested in the Miller (2018) , I use the following categories to label asserters as PAEs: 1,4 and 5. Although this data provides an important advantage to observe litigation behaviour, it is important to highlight the potential drawbacks of merging this dataset with Compustat. First, merging of these datasets is performed over the firm names. Since firm names can change over time in Compustat (see e.g., Arora et al., 2021), and alternative dataset might not update the firm names as exactly appears in Compustat, the matching over firm names is not very reliable. Additionally, firm names can be spelled differently across these databases even there is no change in the firm names. To increase the number of exact matches, I cleaned non-alphabetic characters in company names such as comma and hyphen. Then, I remove all abbreviated words, such as "Hldgs" and "Hldg" (which stand for the original words "Holdings" and "Holding"), as well as their corresponding original words. I also try an alternative method with the fuzzy string matching however, this method did not provide a better matching. Second, unfortunately, the outcome of the litigation cases are not observed in this dataset. Since the process and outcome of litigation might alter firms' cash & debt decisions, investigating the impact litigation on firm cash holding might be problematic. Third, although state laws are primarily designed to address demand letters, they can potentially influence litigation behavior (See Section 1.1, and Section 1.2 for detailed information.) Finally, as suggested by Lemley et al. (2018) patent litigation only provides one side of PAEs activities due to lack of full database on demand letters and licensing agreements. Despite being aware of these concerns and lacking a method to address them, I proceed with a simple procedure. I first constructed firm level probability of being targeted by PAEs.[1] In order to compute the firm-level probability of being targeted by PAEs, I investigate the impact of firm-level variables such as cash holdings, dividend status, market-to-book ratio, R&D stock, sector fixed effects etc., on whether firms are subjected to litigation by PAEs. To calculate this, I only consider the average of firm level controls before the introduction of initial state law. As dependent variable, I use a binary indicator takes value of 1 if firm is litigated by PAEs before the introduction of state-laws.[2] Then I separate firms into two groups depending on the median probability of being targeted by PAEs. After estimating baseline equation 1.1 with two groups, I observe that results are more pronounced when sample is restricted to the firms with high probability of being targeted before the state-laws. I perform this analyses with simple OLS and Logit. The OLS results are presented in the Table A.5.1 below. Results with the Logit are similar and they are available upon request. First three columns presents the results for the firms with relatively high probability of being targeted by PAEs before laws, while the last three columns present the results for the firms with relatively low probability. Results suggest that the firms with relatively high probability of being targeted by PAEs before laws, drive the results.

[1] Instead of calculating probability, I investigate, the impact on firms litigated and non-litigated before state laws by separating sample into two groups. While the statistical significance for the firms litigated by PAEs is not strong (due to small sample size), the economic significance is non-negligible. To avoid this problem and provide more reliable framework, I construct the probability of being targeted by PAEs by using the firm controls before the state laws.

[2] Note that I do not calculate firm-year level litigation probability due to small the number of observations litigated by PAEs.

Table A.5.1: Effect of the Anti-patent Trolling Laws on the Cash & Net Leverage: Probability of Being Targeted by PAEs

	High Prob. of being litigated by PAEs			Low Prob. of being litigated by PAEs		
	Cash/Asset	Cash/N.Asset	N.Leverage	Cash/Asset	Cash/N.Asset	N.Leverage
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
PostEvent	0.0147**	0.0711*	-0.0255*	0.0015	0.1382	-0.0318
	(0.0058)	(0.0367)	(0.0147)	(0.0098)	(0.0884)	(0.0193)
Fixed-effects						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	6,905	6,905	6,905	6,708	6,708	6,708
R^2	0.84667	0.72297	0.87321	0.88545	0.75551	0.80571
Mean	0.1874	0.3527	0.0493	0.2088	0.5911	0.0344

Note. Clustered (State) standard-errors in parentheses. *p<0.1; **p<0.05; ***p<0.01. First three columns presents the results for the firms with high probability of being targeted by PAEs before laws, while the last three columns presents the results for the firms with relatively low probability of being targeted by PAEs before laws.

I also consider constructing a variable at the industry level which takes value of 1 if any of the firms in a 4-digit SIC industry is ever litigated by PAEs before the state-laws. Then I separate the sample into two groups and estimate the baseline equation 1.1. As before, I observe that the firms operating in industries that is previously exposed PAEs litigation drives the results. These results are available upon request.

Finally, I consider yearly binary indicator takes value of 1 if firm is litigated by PAEs status at time t. I interact these variable with the PostEvent indicator. These results are presented in the Table A.5.2 below.

Table A.5.2: Effect of the Anti-patent Trolling Laws on the Cash & Net Leverage: Litigation by PAEs

	All Sample			Only Innovative Firms		
	Cash/Asset	Cash/N.Asset	N.Leverage	Cash/Asset	Cash/N.Asset	N.Leverage
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
PostEvent	0.0063	0.0761*	-0.0235**	0.0139*	0.1358*	-0.0493***
	(0.0047)	(0.0424)	(0.0101)	(0.0079)	(0.0696)	(0.0165)
Litigated	-0.0075**	-0.0373**	0.0051	-0.0088**	-0.0423*	0.0002
	(0.0028)	(0.0163)	(0.0040)	(0.0041)	(0.0245)	(0.0065)
PostEvent × Litigated	0.0117*	0.0648**	-0.0037	0.0202*	0.1109**	-0.0190
	(0.0067)	(0.0281)	(0.0181)	(0.0102)	(0.0517)	(0.0219)
Fixed-effects						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	15,103	15,103	15,103	8,870	8,870	8,870
R^2	0.89047	0.77743	0.85514	0.88564	0.75979	0.82978
Mean	0.2063	0.5216	0.0386	0.2646	0.7273	-0.0560

Note. Clustered (State) standard-errors in parentheses. *p<0.1; **p<0.05; ***p<0.01. First three columns present the results for the all sample while the last three column shows the results when sample is restricted to the innovative firms as in Section 1.5.

I also consider being litigated by PAEs as a control variable in the baseline estimations. In addition, I investigate whether the being litigated by PAEs affects the introduction of state laws as in Table A.4.1. Results are robust to these specifications and available upon request.

Table A.6.1: Alternative controls: Log Assets and Lag dependent variable

Dependent Variables:	Cash/Asset	Cash/N.Asset	N.Leverage	Cash/Asset	Cash/N.Asset	N.Leverage
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
PostEvent	0.0135**	0.1216**	-0.0332***	0.0090**	0.0648**	-0.0152**
	(0.0054)	(0.0557)	(0.0123)	(0.0041)	(0.0320)	(0.0066)
Fixed-effects & Controls						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	15,103	15,103	15,103	12,890	12,890	12,890
R^2	0.87203	0.75739	0.83351	0.89260	0.80744	0.87598
Mean	0.2063	0.5216	0.0386	0.2016	0.4848	0.0436

Note. Clustered (State) standard-errors in parentheses. *p<0.1; **p<0.05; ***p<0.01. Firm controls include cash flow, capital expenditure, acquisitions (all normalized by assets), market to book ratio, R&D report dummy, log assets (column 1-3) or log employment (column 3-6), dividend paying status in any given year and industry cash flow volatility.

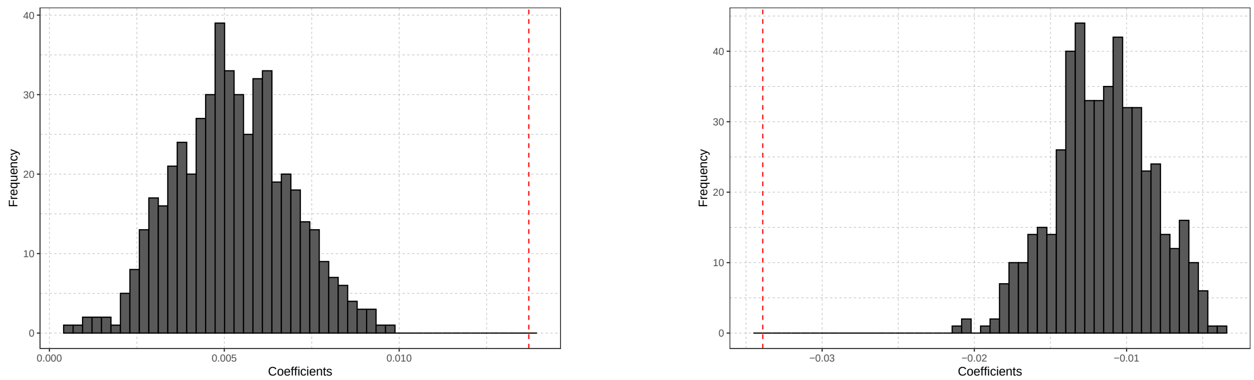
A.6 Robustness Checks

Table A.6.2: Sample Adjustments: Limit the sample

		All sample			Innovative	
Dependent Variables:	Cash/Asset	Cash/N.Asset	N.Leverage	Cash/Asset	Cash/N.Asset	N.Leverage
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
PostEvent	0.0113**	0.1085**	-0.0307***	0.0139**	0.1417**	-0.0512***
	(0.0047)	(0.0485)	(0.0113)	(0.0067)	(0.0639)	(0.0155)
Fixed-effects & Controls						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	11,618	11,618	11,618	6,792	6,792	6,792
R^2	0.89005	0.77785	0.85025	0.88456	0.75743	0.82326
Mean	0.2048	0.5240	0.0508	0.2635	0.7274	-0.0426

Note. Clustered (State) standard-errors in parentheses. *p<0.1; **p<0.05; ***p<0.01. Firm controls include cash flow, capital expenditure, acquisitions (all normalized by assets), market to book ratio, R&D report dummy, log employment, dividend paying status in any given year and industry cash flow volatility. The first three column uses the whole sample for the period between 2012-2019 while the last three column focuses on only innovative firms.

Figure A.6.1: Falsification Test



Note. This figure plots a histogram of coefficients from a regression of firms' cash and net leverage on a counterfactual anti-patent trolling law indicator. The distribution of coefficients is obtained from 100 counterfactual randomly generated the anti-patent trolling laws adoption year assignment. I estimate the baseline equation 1.1 500 times with the randomly generated adoption years (between 2010-2019) of anti-patent trolling laws. If a state never adopted an anti-patent trolling law, it is always assigned to the control group. Red dashed line represents the baseline regression estimates. Regressions include firm fixed and year effects. Standard errors are clustered at the state level.

Table A.6.3: Excluding Treatment Cohorts

	2014			2015			2016			2017		
	Cash/Asset	Cash/N.Asset	N.Leverage	Cash/Asset	Cash/N.Asset	N.Leverage	Cash/Asset	Cash/N.Asset	N.Leverage	Cash/Asset	Cash/N.Asset	N.Leverage
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Variables												
PostEvent	0.0183**	0.1329**	-0.0254	0.0096*	0.1034*	-0.0378***	0.0162***	0.1320**	-0.0388***	0.0142***	0.1259**	-0.0350***
	(0.0081)	(0.0621)	(0.0160)	(0.0053)	(0.0546)	(0.0136)	(0.0047)	(0.0528)	(0.0125)	(0.0049)	(0.0512)	(0.0116)
Fixed-effects & Controls												
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics												
Observations	11,689	11,689	11,689	11,756	11,756	11,756	14,335	14,335	14,335	14,802	14,802	14,802
R^2	0.86618	0.74775	0.81782	0.88200	0.76666	0.84341	0.87768	0.76103	0.83708	0.87618	0.76063	0.83178
Mean	0.2231	0.5895	0.0196	0.2193	0.5714	0.0166	0.2066	0.5284	0.0398	0.2078	0.5275	0.0359

Note. Clustered (State) standard-errors in parentheses. *p<0.1; **p<0.05; ***p<0.01. Firm controls include cash flow, capital expenditure, acquisitions (all normalized by assets), market to book ratio, R&D report dummy, log employment, dividend paying status in any given year and industry cash flow volatility.

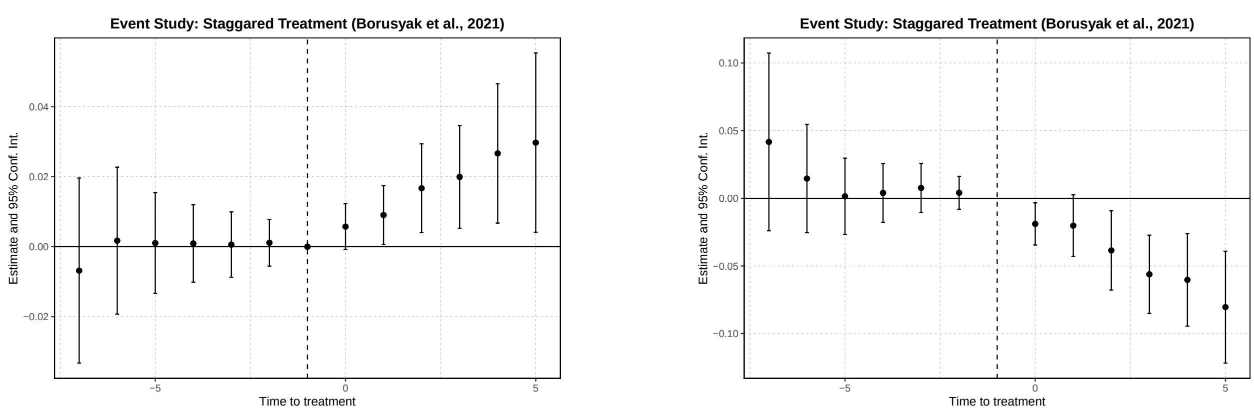
Table A.6.4: Balancing Table-Entropy Balancing

	Dependent variable:						
	Acq.	Cashflow	CapitalExp.	MTB	Dividend	R&D Stock/Assets	Log(Emp)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treatment Status	0.00000	0.00000	0.00000	−0.00001	0.00000	−0.00001	0.00002
	(0.002)	(0.009)	(0.004)	(0.064)	(0.023)	(0.027)	(0.100)
Observations	1,867	1,867	1,867	1,867	1,867	1,867	1,867
R^2	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Table A.6.5: Balancing Table-Propensity Score Reweighing

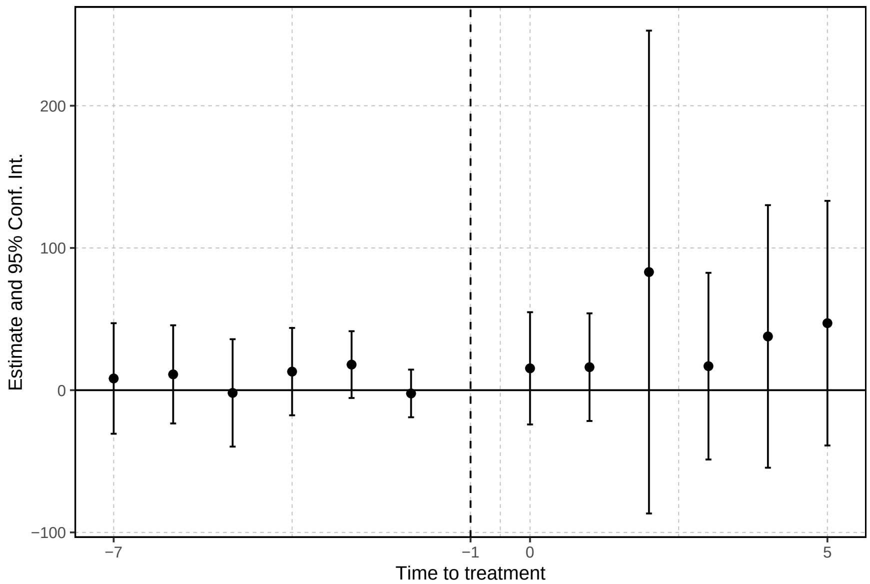
	Dependent variable:						
	Acq.	Cashflow	CapitalExp.	MTB	Dividend	R&D Stock/Assets	Log(Emp)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treatment Status	0.0003	−0.00005	0.002	0.012	−0.002	−0.004	−0.006
	(0.002)	(0.010)	(0.003)	(0.072)	(0.022)	(0.023)	(0.017)
Observations	1,864	1,864	1,864	1,864	1,864	1,864	1,864
R^2	0.00002	0.000	0.0004	0.00002	0.00000	0.00002	0.0001

Figure A.6.2: Baseline Results with Borusyak et al. (2022)



Note.The dependent variables are Cash/Asset and N.Leverage. The omitted category is 1 year before the enactment of the law. Estimates of the treatment effect dynamics are obtained from the imputation estimator proposed by Borusyak et al. (2022). The omitted category is the one year before the treatment. The error bars represent 95% confidence intervals. Regressions include firm and year fixed effects. Standard errors are clustered at the state level.

Figure A.6.3: Impact on External Finance Dependence Index



Note. The dependent variables are Cash/Asset at the firm level. The omitted category is 1 year before the enactment of the law. The error bars represent 95% confidence intervals. Regressions include firm and year fixed effects and controls. Standard errors are clustered at the state level.

Appendix B

Appendix to Chapter 2

B.1 Lobby Report

Figure B.1.1: An example of lobbying report

LD-2 Disclosure Form 26.05.2021 17:00

Clerk of the House of Representatives Legislative Resource Center 135 Cannon Building Washington, DC 20515 http://lobbyingdisclosure.house.gov	Secretary of the Senate Office of Public Records 232 Hart Building Washington, DC 20510 http://www.senate.gov/lobby

LOBBYING REPORT

Lobbying Disclosure Act of 1995 (Section 5) - **All Filers Are Required to Complete This Page**

1. Registrant Name [x] Organization/Lobbying Firm [ ] Self Employed Individual
JOHNSON & JOHNSON SERVICES, INC.

2. Address
Address1 ONE JOHNSON & JOHNSON PLAZA Address2
City NEW BRUNSWICK State NJ Zip Code 08933 Country USA

3. Principal place of business (if different than line 2)
City State Zip Code Country

4a. Contact Name Mr. CLIFFORD HOLLAND
b. Telephone Number 7325242884
c. E-mail chollan@its.jnj.com

5. Senate ID# 20686-12

7. Client Name [x] *Self* [ ] *Check if client is a state or local government or instrumentality*
JOHNSON & JOHNSON SERVICES, INC.

6. House ID# 303480000

TYPE OF REPORT 8. Year 2012 Q1 (1/1 - 3/31) [x] Q2 (4/1 - 6/30) [ ] Q3 (7/1 - 9/30) [ ] Q4 (10/1 - 12/31) [ ]

9. Check if this filing amends a previously filed version of this report [ ]

10. Check if this is a Termination Report [ ] Termination Date ______ 11. No Lobbying Issue Activity [ ]

INCOME OR EXPENSES - YOU MUST complete either Line 12 or Line 13

12. Lobbying

INCOME relating to lobbying activities for this reporting period was:

Less than $5,000 [ ]

$5,000 or more [ ] $ ______

Provide a good faith estimate, rounded to the nearest $10,000, of all lobbying related income for the client (including all payments to the registrant by any other entity for lobbying activities on behalf of the client).

13. Organizations

EXPENSE relating to lobbying activities for this reporting period were:

Less than $5,000 [ ]

$5,000 or more [x] $ 2,260,000.00

14. REPORTING Check box to indicate expense accounting method. See instructions for description of options.

[x] **Method A.** Reporting amounts using LDA definitions only

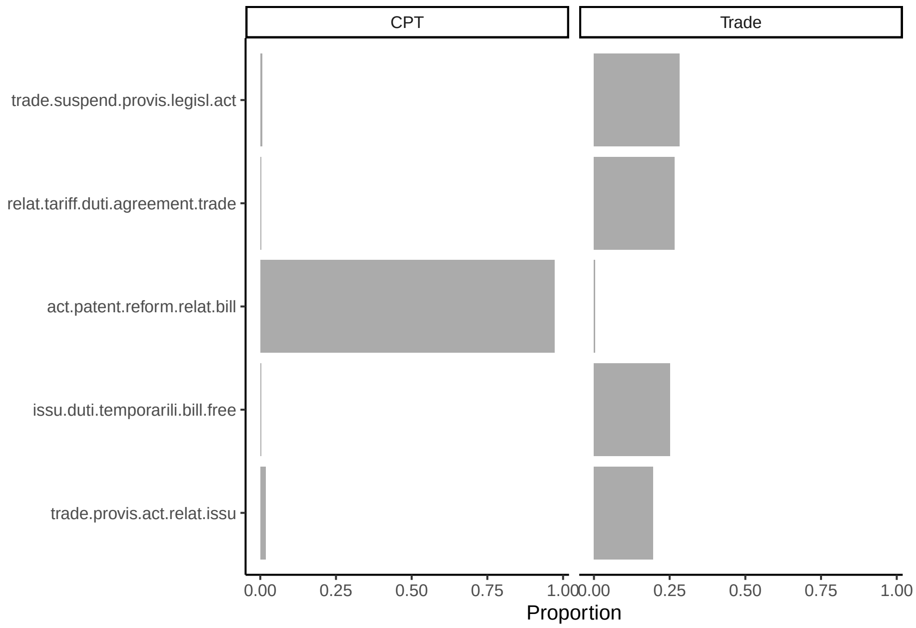
[ ] **Method B.** Reporting amounts under section 6033(b)(8) of the Internal Revenue Code

[ ] **Method C.** Reporting amounts under section 162(e) of the Internal Revenue Code

Signature Digitally Signed By: Clifford Holland, Corporate Vice President, Government Affairs and Policy **Date** 04/20/2012

B.2 Topic Modelling

Figure B.2.1: Topic modelling for trade and IPR related reports for 2008



B.3 Additional Empirical Analyses

Table B.3.1: Import Penetration from China and IPR Lobbying: Without Control Variables

Model:	Lobby(Binary) (1) OLS	#Reports (2) Poisson	Amount (3) OLS	Lobby(Binary) (4) IV	#Reports (5) IV	Amount (6) IV
Variables						
ImportShare	0.0576***	3.934***	0.6239***	0.0909***	4.375***	1.026***
	(0.0194)	(0.9381)	(0.2342)	(0.0243)	(0.8958)	(0.2954)
Fixed-effects & Controls						
SIC	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	No	No	No
Fit statistics						
Observations	14,668	8,823	14,668	14,668	8,823	14,668
R^2	0.03582		0.03556	0.03616		0.03594
Pseudo R^2		0.10977			0.10983	
				First-Stage Estimates		
Coef-Instrument				1.0705***	1.0738***	1.0705***
				(0.041)	(0.0324)	(0.041)
F-test (1st stage)				682.1	1,101.1	682.1

Note. Clustered (SIC3) standard-errors in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table B.3.2: Import Penetration from China and IPR Lobbying: Probit

Model:	Probit Lobby(Binary) (1)	 (2)
Variables		
ImportShare	2.244***	2.359***
	(0.6546)	(0.8279)
Fixed-effects & Controls		
SIC	Yes	Yes
Year	Yes	Yes
Controls	Yes	Yes
Fit statistics		
Observations	8,823	8,823
Pseudo R^2	0.50507	0.50488
	First-Stage Estimates	
Coef-Instrument		1.0636***
		(0.0304)
F-test (1st stage)		166.8

Note. Clustered (SIC3) standard-errors in parentheses. *p<0.1; **p<0.05; ***p<0.01. Firm controls include log employment, log sales per worker, HHI, log patent stock, binary indicator takes value of 1 if firm lobbies on other issues at time t, binary variable for foreign income, industry-year level export share of US to China and the log of the rest of the employment in the industry.

Table B.3.3: Import Penetration from China and IPR Lobbying: All Sectors

Model:	Lobby(Binary) (1) OLS	#Reports (2) Poisson	Amount (3) OLS	Lobby(Binary) (4) IV	#Reports (5) IV	Amount (6) IV
Variables						
ImportShare	0.0624***	4.390***	0.6879***	0.0966***	5.154***	1.108***
	(0.0172)	(1.003)	(0.2036)	(0.0205)	(1.052)	(0.2453)
Fixed-effects & Controls						
SIC	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	15,946	8,908	15,946	15,946	8,908	15,946
R^2	0.03647		0.03608	0.03687		0.03653
Pseudo R^2		0.11003			0.11056	
			First-Stage Estimates			
Coef-Instrument				1.0763***	1.0746***	1.0763***
				(0.038)	(0.0323)	(0.038)
F-test (1st stage)				802.9	1,104.7	802.9

Note. Clustered (SIC3) standard-errors in parentheses. *p<0.1; **p<0.05; ***p<0.01. Firm controls include log employment, log sales per worker, HHI, log patent stock, binary indicator takes value of 1 if firm lobbies on other issues at time t, binary variable for foreign income, industry-year level export share of US to China and the log of the rest of the employment in the industry.

Table B.3.4: Import Penetration from China and IPR Lobbying: Productive vs non-Productive Firms

	non-Productive Firms			Productive Firms		
Model:	Lobby(Binary) (1) OLS	#Reports (2) Poisson	Amount (3) OLS	Lobby(Binary) (4) OLS	#Reports (5) Poisson	Amount (6) OLS
Variables						
ImportShare	-0.0004	-8.204	-0.0054	0.0844**	3.003***	0.8623*
	(0.0135)	(11.52)	(0.1588)	(0.0361)	(0.8096)	(0.4423)
Fixed-effects & Controls						
SIC	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	7,078	2,627	7,078	7,590	4,416	7,590
R^2	0.13493		0.12886	0.16542		0.16723
Pseudo R^2		0.53616			0.62398	

Note. Clustered (SIC3) standard-errors in parentheses. *p<0.1; **p<0.05; ***p<0.01. Firm controls include log employment, log sales per worker, HHI, log patent stock, binary indicator takes value of 1 if firm lobbies on other issues at time t, binary variable for foreign income, industry-year level export share of US to China and the log of the rest of the employment in the industry.

Table B.3.5: Import Penetration from China and IPR Lobbying-Productivity: Instrumental Variable

Model:	Lobby(Binary) (1)	#Reports (2)	Amount (3)
Variables			
ImportShare	0.1495***	3.295***	1.668***
	(0.0456)	(1.156)	(0.5660)
Fixed-effects & Controls			
SIC	Yes	Yes	Yes
Year	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Fit statistics			
Observations	7,590	4,416	7,590
R^2	0.16615		0.16803
Pseudo R^2		0.62362	
	First-Stage Estimates		
Coef.-Instrument	1.0521***	1.0684***	1.0521***
	(0.0339)	(0.0304)	(0.0339)
F-test (1st stage)	964.7	263.5	964.7

Note. Clustered (SIC3) standard-errors in parentheses. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$. Firm controls include log employment, log sales per worker, HHI, log patent stock, binary indicator takes value of 1 if firm lobbies on other issues at time t, binary variable for foreign income, industry-year level export share of US to China and the log of the rest of the employment in the industry.

Table B.3.6: Import Penetration from China and IPR Lobbying-Import Intensity: Instrumental Variable

Model:	Lobby(Binary) (1)	#Reports (2)	Amount (3)
Variables			
ImportShare	0.1419***	8.624***	1.663***
	(0.0382)	(2.306)	(0.4670)
Fixed-effects & Controls			
SIC	Yes	Yes	Yes
Year	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Fit statistics			
Observations	5,848	2,404	5,848
R^2	0.13286		0.13902
Pseudo R^2		0.70110	
	First-Stage Estimates		
Coef.-Instrument	0.8796***	0.849***	0.8796***
	(0.0763)	(0.0968)	(0.0763)
F-test (1st stage)	132.9	87.54	132.9

Note. Clustered (SIC3) standard-errors in parentheses. *p<0.1; **p<0.05; ***p<0.01. Firm controls include log employment, log sales per worker, HHI, log patent stock, binary indicator takes value of 1 if firm lobbies on other issues at time t, binary variable for foreign income, industry-year level export share of US to China and the log of the rest of the employment in the industry.

Appendix C

Appendix to Chapter 3

C.1 Additional Empirical Analyses

Table C.1.1: Determinants of Digital Adoption: Probit

Dependent Variable:	Digital			
Model:	(1)	(2)	(3)	(4)
Variables				
ln(VA/Emp)	0.1896***	0.1726***	0.1402***	0.1072***
	(0.0157)	(0.0138)	(0.0222)	(0.0235)
ln(Emp)		0.1967***	0.1959***	0.1830***
		(0.0084)	(0.0084)	(0.0089)
ln(wage/Emp)			0.0455**	0.0604**
			(0.0212)	(0.0237)
Exporter				0.2301***
				(0.0274)
Innovation investment share				0.3639***
				(0.0382)
Fixed-effects				
Sector	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes
Fit statistics				
Observations	23,772	23,772	23,772	20,349
Pseudo R^2	0.05624	0.08446	0.08459	0.09318

Note. Clustered (Country & Sector (CPA1)) standard-errors in parentheses. *p<0.1; **p<0.05; ***p<0.01. The last column also include age categories as control variable.

Table C.1.2: Effect of Digital Adoption on Firms' Training & Management Practices & Innovation: IV Probit

Variables	(1) Training	(2) Mngmt Prac.	(3) Innov.(Binary)
Digital	1.927***	0.693**	1.199***
	(0.301)	(0.286)	(0.303)
Fixed-effects & Controls			
Controls	Yes	Yes	Yes
Country	Yes	Yes	Yes
Sector	Yes	Yes	Yes
Year	Yes	Yes	Yes
Fit statistics			
Observations	38,062	41,525	35,133

Note. Clustered (Country & Sector (CPA1)) standard-errors in parentheses. *p<0.1; **p<0.05; ***p<0.01. The table reports the estimates from IV-Probit. Controls include exporter status, age and size categories.

Table C.1.3: Effect of Digital Adoption on Firms' Training & Management Practices: Alternative Controls

Model:	Lag controls		Alternative Controls	
Dependent Variables:	Training	Mngmt Prac.	Training	Mngmt Prac.
Model:	(1)	(2)	(3)	(4)
Variables				
Digital	0.4185***	0.1872	1.039***	0.3494
	(0.1410)	(0.1626)	(0.3556)	(0.3050)
Fixed-effects & Controls				
Wave	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Fit statistics				
Observations	16,422	17,251	38,066	41,529
	First-Stage Estimates			
Ln(Upstream(Digital)Patent)	0.0323***	0.0268***	0.0398***	0.0331***
	(0.0097)	(0.0097)	(0.0121)	(0.0116)
Ln(Downstream(Digital)Patent)	0.0348***	0.0334***	0.0114	0.0108
	(0.0084)	(0.0079)	(0.0163)	(0.0156)
R^2 (1st stage)	0.12302	0.12158	0.11308	0.11257
F-test (1st stage)	39.396	34.129	13.808	10.907

Note. Clustered (Country & Sector (CPA1)) standard-errors in parentheses. *p<0.1; **p<0.05; ***p<0.01. First two column includes the lag employment, lag capital intensity, exporter status and age categories. The last two column uses add the log of non-digital upstream and downstream weighted patents as controls along with exporter status, age and size categories. Same controls are used in the first stage. Kleibergen-Paap Wald F-stat is reported for the first stage.

Table C.1.4: Effect of Digital Adoption on Firms' Innovation:Alternative Controls

Model:	Lag Controls		Alternative Controls	
Dependent Variables:	Innov.(Binary)	Innov.(Share)	Innov.(Binary)	Innov.(Share)
Model:	(1)	(2)	(3)	(4)
Variables				
Digital	0.3599**	0.3019***	1.504***	0.9186***
	(0.1587)	(0.0758)	(0.4688)	(0.2900)
Fixed-effects & Controls				
Wave	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Fit statistics				
Observations	15,271	15,271	35,135	35,135
	First-Stage Estimates			
Ln(Upstream(Digital)Patent)	0.0252***	0.0252***	0.0303**	0.0303**
	(0.0091)	(0.0091)	(0.0125)	(0.0125)
Ln(Downstream(Digital)Patent)	0.0360***	0.0360***	0.0166	0.0166
	(0.0085)	(0.0085)	(0.0162)	(0.0162)
R^2	0.11853	0.11853	0.11108	0.11108
F-test (1st stage)	32.544	32.544	9.8120	9.8120

Note. Clustered (Country & Sector (CPA1)) standard-errors in parentheses. *p<0.1; **p<0.05; ***p<0.01. First two column includes the lag employment, lag capital intensity, exporter status and age categories. The last two column uses add the log of non-digital upstream and downstream weighted patents as controls along with exporter status, age and size categories. Same controls are used in the first stage. Kleibergen-Paap Wald F-stat is reported for the first stage.

Table C.1.5: Effect of Digital Adoption on Firms' Training & Management Practices: Manufacturing Firms and Alternative Instruments

Model:	Manufacturing Firms		Alternative Instruments	
Dependent Variables:	Training	Mngmt Prac.	Training	Mngmt Prac.
Model:	(1)	(2)	(3)	(4)
Variables				
Digital	0.6076***	0.2924***	0.6613*	0.1742
	(0.1246)	(0.0967)	(0.3976)	(0.3802)
Fixed-effects & Controls				
Wave	Yes	Yes	Yes	Yes
Sector			Yes	Yes
Country	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Fit statistics				
Observations	11,791	12,830	38,066	41,529
	First-Stage Estimates			
Ln(Upstream(Digital)Patent)	0.0237**	0.0169*		
	(0.0092)	(0.0087)		
Ln(Downstream(Digital)Patent)	0.0470***	0.0457***		
	(0.0097)	(0.0086)		
Share (Upstream)			0.1228**	0.0974*
			(0.0546)	(0.0522)
Share (Downstream)			0.0825	0.0748
			(0.0719)	(0.0688)
R^2 (1st stage)	0.12844	0.12636	0.11079	0.11069
F-test (1st stage)	74.572	66.838	10.116	7.5585

Note. Clustered (Country & Sector (CPA1)) standard-errors in parentheses. *p<0.1; **p<0.05; ***p<0.01. Controls include exporter status, age and size categories. Same controls are used in the first stage. Kleibergen-Paap Wald F-stat is reported for the first stage.

Table C.1.6: Effect of Digital Adoption on Firms' Innovation: Manufacturing Firms and Alternative Instruments

Model: Alternative instruments	Manufacturing Firms			
Dependent Variables:	Innov.(Binary)	Innov.(Share)	Innov.(Binary)	Innov.(Share)
Model:	(1)	(2)	(3)	(4)
Variables				
Digital	0.4176***	0.2958***	1.616***	0.9734***
	(0.1347)	(0.0749)	(0.5323)	(0.3358)
Fixed-effects & Controls				
Wave	Yes	Yes	Yes	Yes
Sector			Yes	Yes
Country	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Fit statistics				
Observations	11,172	11,172	35,135	35,135
	First-Stage Estimates			
Ln(Upstream(Digital)Patent)	0.0194*	0.0194*		
	(0.0099)	(0.0099)		
Ln(Downstream(Digital)Patent)	0.0462***	0.0462***		
	(0.0102)	(0.0102)		
Upstream(Digital) Patent Share			0.0925*	0.0925*
			(0.0560)	(0.0560)
Downstream(Digital) Patent Share			0.1069	0.1069
			(0.0708)	(0.0708)
R^2 (1st stage)	0.11971	0.11971	0.10913	0.10913
F-test (1st stage)	63.537	63.537	8.0902	8.0902

Note. Clustered (Country & Sector (CPA1)) standard-errors in parentheses. *p<0.1; **p<0.05; ***p<0.01. Controls include exporter status, age and size categories. Same controls are used in the first stage. Kleibergen-Paap Wald F-stat is reported for the first stage.

Table C.1.7: Effect of Digital Adoption on Firms' Outcome: Alternative Digital Specification

Model:	Alternative digital patent specification						
Dependent Variables:	ln(VA/Emp)	ln(TFP)	ln(wage/emp)	Training	Mngmt Prac.	Innov.(Binary)	Innov.(Share)
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables							
Digital	1.484***	1.680***	1.661***	0.6767***	0.2525*	0.4103***	0.3439***
	(0.4013)	(0.4057)	(0.3429)	(0.1588)	(0.1353)	(0.1442)	(0.0867)
Fixed-effects & Controls							
Wave	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics							
Observations	36,058	34,617	39,275	38,066	41,529	35,135	35,135
	First-Stage Estimates						
Ln(Upstream(Digital)Patent)	0.0232***	0.0242***	0.0227***	0.0288***	0.0244***	0.0196***	0.0196***
	(0.0067)	(0.0068)	(0.0066)	(0.0069)	(0.0068)	(0.0070)	(0.0070)
Ln(Downstream(Digital)Patent)	0.0226***	0.0220***	0.0238***	0.0257***	0.0244***	0.0286***	0.0286***
	(0.0068)	(0.0068)	(0.0069)	(0.0070)	(0.0065)	(0.0070)	(0.0070)
R^2	0.10889	0.10778	0.11216	0.11308	0.11260	0.11108	0.11108
F-test (1st stage)	40.491	39.295	45.827	59.264	52.370	46.529	46.529

Note. Clustered (Country & Sector (CPA1)) standard-errors in parentheses. *p<0.1; **p<0.05; ***p<0.01. Controls include exporter status, age and size categories. Same controls are used in the first stage. Kleibergen-Paap Wald F-stat is reported for the first stage.

Table C.1.8: Effect of Digital Adoption on Firms' Outcome: Western & Northern Europe and Southern Europe

Model:	Western & Northern Europe			Southern Europe		
Dependent Variables:	ln(VA/Emp) (1)	ln(TFP) (2)	ln(wage/emp) (3)	ln(VA/Emp) (4)	ln(TFP) (5)	ln(wage/emp) (6)
Variables						
Digital	0.7695	1.519	1.384**	1.614***	1.691***	1.421***
	(0.8896)	(1.196)	(0.6020)	(0.5311)	(0.5433)	(0.4032)
Fixed-effects & Controls						
Wave	Yes	Yes	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	13,782	13,099	15,032	7,559	7,326	8,286
First-Stage Estimates						
Ln(Upstream(Digital)Patent)	0.0212**	0.0196**	0.0240***	0.0241*	0.0287**	0.0202
	(0.0088)	(0.0091)	(0.0089)	(0.0130)	(0.0133)	(0.0138)
Ln(Downstream(Digital)Patent)	0.0087	0.0072	0.0116	0.0344***	0.0348***	0.0352***
	(0.0112)	(0.0113)	(0.0117)	(0.0129)	(0.0125)	(0.0126)
R^2	0.13425	0.13359	0.13724	0.09258	0.09060	0.09526
F-test (1st stage)	6.1852	4.7432	9.5353	14.183	15.545	14.647

Note. Clustered (Country & Sector (CPA1)) standard-errors in parentheses. *p<0.1; **p<0.05; ***p<0.01. Controls include exporter status, age and size categories. Same controls are used in the first stage. Kleibergen-Paap Wald F-stat is reported for the first stage.

Table C.1.9: Effect of Digital Adoption on Firms' Outcome: Western & Northern Europe and Southern Europe

Model:	Western & Northern Europe		Southern Europe	
Dependent Variables:	Training (1)	Mngmt Prac. (2)	Training (3)	Mngmt Prac. (4)
Variables				
Digital	0.8031**	-0.3195	0.6405**	0.5196**
	(0.4020)	(0.4266)	(0.2987)	(0.2140)
Fixed-effects & Controls				
Wave	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Fit statistics				
Observations	14,763	16,223	7,789	8,461
	First-Stage Estimates			
Ln(Upstream(Digital)Patent)	0.0232**	0.0249***	0.0271**	0.0231*
	(0.0090)	(0.0086)	(0.0128)	(0.0138)
Ln(Downstream(Digital)Patent)	0.0152	0.0128	0.0379***	0.0355***
	(0.0118)	(0.0114)	(0.0125)	(0.0115)
R^2 (1st stage)	0.13738	0.13778	0.09698	0.09353
F-test (1st stage)	10.712	11.272	17.725	15.801

Note. Clustered (Country & Sector (CPA1)) standard-errors in parentheses. *p<0.1; **p<0.05; ***p<0.01. Controls include exporter status, age and size categories. Same controls are used in the first stage. Kleibergen-Paap Wald F-stat is reported for the first stage.

Table C.1.10: Effect of Digital Adoption on Firms' Outcome: Western & Northern Europe and Southern Europe

Model:	Western & Northern Europe		Southern Europe	
Dependent Variables:	Innov.(Binary)	Innov.(Share)	Innov.(Binary)	Innov.(Share)
Model:	(1)	(2)	(3)	(4)
Variables				
Digital	0.2264	0.4327*	0.4224*	0.3751**
	(0.2971)	(0.2373)	(0.2169)	(0.1748)
Fixed-effects & Controls				
Wave	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Fit statistics				
Observations	13,721	13,721	7,156	7,156
	First-Stage Estimates			
Ln(Upstream(Digital)Patent)	0.0187*	0.0187*	0.0198	0.0198
	(0.0101)	(0.0101)	(0.0157)	(0.0157)
Ln(Downstream(Digital)Patent)	0.0175	0.0175	0.0383***	0.0383***
	(0.0116)	(0.0116)	(0.0129)	(0.0129)
R^2	0.13439	0.13439	0.08952	0.08952
F-test (1st stage)	9.3619	9.3619	14.769	14.769

Note. Clustered (Country & Sector (CPA1)) standard-errors in parentheses. *p<0.1; **p<0.05; ***p<0.01. Controls include exporter status, age and size categories. Same controls are used in the first stage. Kleibergen-Paap Wald F-stat is reported for the first stage.

Table C.1.11: Effect of Digital Adoption on Firms' Outcome: Central and East Europe

Model:	Central and East Europe						
Dependent Variables:	ln(VA/Emp)	ln(TFP)	ln(wage/emp)	Training	Mngmt Prac.	Innov.(Binary)	Innov.(Share)
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables							
Digital	1.839***	1.840***	2.013***	0.7388***	0.4155**	0.7240**	0.3237***
	(0.6199)	(0.5986)	(0.6492)	(0.2212)	(0.1684)	(0.2990)	(0.1089)
Fixed-effects & Controls							
Wave	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics							
Observations	14,717	14,192	15,957	15,514	16,845	14,258	14,258
	First-Stage Estimates						
Ln(Upstream(Digital)Patent)	0.0241**	0.0260**	0.0233**	0.0335***	0.0238**	0.0208*	0.0208*
	(0.0104)	(0.0105)	(0.0105)	(0.0112)	(0.0109)	(0.0111)	(0.0111)
Ln(Downstream(Digital)Patent)	0.0255**	0.0240**	0.0239**	0.0256**	0.0246**	0.0305**	0.0305**
	(0.0118)	(0.0116)	(0.0118)	(0.0117)	(0.0111)	(0.0122)	(0.0122)
R^2 (1st stage)	0.09915	0.09838	0.10284	0.10343	0.10336	0.10384	0.10384
F-test (1st stage)	18.242	17.879	17.882	27.060	19.817	19.472	19.472

Note. Clustered (Country & Sector (CPA1)) standard-errors in parentheses. *p<0.1; **p<0.05; ***p<0.01. Controls include exporter status, age and size categories. Same controls are used in the first stage. Kleibergen-Paap Wald F-stat is reported for the first stage.

Table C.1.12: Effect of Digital Adoption on Firms' Outcome: Only with Upstream & Downstream

Model:	Only with Upstream & Downstream					
Dependent Variables:	ln(VA/Emp) (1)	ln(TFP) (2)	ln(wage/emp) (3)	ln(VA/Emp) (4)	ln(TFP) (5)	ln(wage/emp) (6)
Variables						
Digital	1.600***	1.814***	1.975***	1.384***	1.621***	1.472***
	(0.4847)	(0.4933)	(0.4438)	(0.4429)	(0.4619)	(0.3661)
Fixed-effects & Controls						
Wave	Yes	Yes	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	36,058	34,617	39,275	36,058	34,617	39,275
	First-Stage Estimates					
Ln(Upstream(Digital)Patent)	0.0334***	0.0342***	0.0334***			
	(0.0071)	(0.0072)	(0.0072)			
Ln(Downstream(Digital)Patent)				0.0297***	0.0294***	0.0309***
				(0.0072)	(0.0072)	(0.0073)
R^2	0.10816	0.10710	0.11137	0.10824	0.10709	0.11154
F-test (1st stage)	51.782	52.005	56.514	54.740	51.592	64.052

Note. Clustered (Country & Sector (CPA1)) standard-errors in parentheses. *p<0.1; **p<0.05; ***p<0.01. Controls include exporter status, age and size categories. Same controls are used in the first stage. Kleibergen-Paap Wald F-stat is reported for the first stage.

Table C.1.13: Effect of Digital Adoption on Firms' Outcome: Only with Upstream & Downstream

Model:	Only with Upstream & Downstream			
Dependent Variables:	Training (1)	Mngmt Prac. (2)	Training (3)	Mngmt Prac. (4)
Variables				
Digital	1.137***	0.4476***	0.2197	0.0584
	(0.2457)	(0.1678)	(0.1521)	(0.1713)
Fixed-effects & Controls				
Wave	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Fit statistics				
Observations	38,066	41,529	38,066	41,529
	First-Stage Estimates			
Ln(Upstream(Digital)Patent)	0.0404***	0.0353***		
	(0.0076)	(0.0074)		
Ln(Downstream(Digital)Patent)			0.0350***	0.0321***
			(0.0075)	(0.0071)
R^2 (1st stage)	0.11217	0.11179	0.11216	0.11190
F-test (1st stage)	79.260	66.592	78.972	72.054

Note. Clustered (Country & Sector (CPA1)) standard-errors in parentheses. *p<0.1; **p<0.05; ***p<0.01. Controls include exporter status, age and size categories. Same controls are used in the first stage. Kleibergen-Paap Wald F-stat is reported for the first stage.

Table C.1.14: Effect of Digital Adoption on Firms' Outcome: Only with Upstream & Downstream

Model:	Only with Upstream & Downstream			
Dependent Variables:	Innov.(Binary)	Innov.(Share)	Innov.(Binary)	Innov.(Share)
Model:	(1)	(2)	(3)	(4)
Variables				
Digital	0.6019***	0.4305***	0.3842**	0.3388***
	(0.2225)	(0.1274)	(0.1493)	(0.0918)
Fixed-effects & Controls				
Wave	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Fit statistics				
Observations	35,135	35,135	35,135	35,135
	First-Stage Estimates			
Ln(Upstream(Digital)Patent)	0.0328***	0.0328***		
	(0.0077)	(0.0077)		
Ln(Downstream(Digital)Patent)			0.0350***	0.0350***
			(0.0074)	(0.0074)
R^2 (1st stage)	0.10996	0.10996	0.11062	0.11062
F-test (1st stage)	48.790	48.790	74.725	74.725

Note. Clustered (Country & Sector (CPA1)) standard-errors in parentheses. *p<0.1; **p<0.05; ***p<0.01. Controls include exporter status, age and size categories. Same controls are used in the first stage. Kleibergen-Paap Wald F-stat is reported for the first stage.

Table C.1.15: Effect of Digital Adoption on Firms' Outcome: Excluding top and bottom one percent

Model:	Excluding top and bottom one percent		
Dependent Variables:	ln(VA/Emp)	ln(TFP)	ln(wage/emp)
Model:	(1)	(2)	(3)
Variables			
Digital	1.442***	1.581***	1.691***
	(0.3816)	(0.3930)	(0.3310)
Fixed-effects & Controls			
Wave	Yes	Yes	Yes
Sector	Yes	Yes	Yes
Country	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Fit statistics			
Observations	35,329	33,923	38,488
	First-Stage Estimates		
Ln(Upstream(Digital)Patent)	0.0233***	0.0238***	0.0244***
	(0.0069)	(0.0070)	(0.0068)
Ln(Downstream(Digital)Patent)	0.0228***	0.0217***	0.0234***
	(0.0069)	(0.0069)	(0.0069)
R^2	0.10975	0.10789	0.11256
F-test (1st stage)	39.081	36.267	45.320

Note. Clustered (Country & Sector (CPA1)) standard-errors in parentheses. *p<0.1; **p<0.05; ***p<0.01. Controls include exporter status, age and size categories. Same controls are used in the first stage. Kleibergen-Paap Wald F-stat is reported for the first stage.

Table C.1.16: Effect of Digital Adoption on Firms' Outcome Without Matching

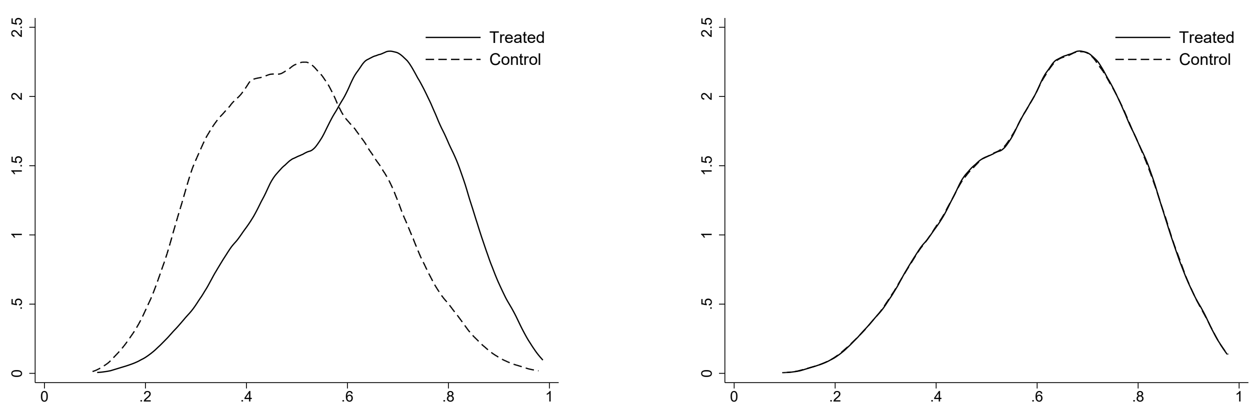
Dependent Variables:	ln(VA/Emp)	ln(TFP)	ln(Wage/Emp)	Training	Mngmt Prac.	Innov.(Binary)	Innov.(Share)
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables							
Digital	0.102***	0.088***	0.064***	0.325***	0.534***	0.357***	0.049***
	(0.012)	(0.010)	(0.011)	(0.028)	(0.026)	(0.030)	(0.006)
Fixed-effects & Controls							
Wave	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	No	No	No	No
Fit statistics							
Observations	11,957	11,957	11,532	11,389	11,786	10,922	10,926
R-squared	0.501	0.598	0.605				0.062
Pseudo R2				0.0941	0.115	0.0637	

Note. Clustered (Country & Sector) standard-errors in parentheses. *p<0.1; **p<0.05; ***p<0.01. Column 4, 5 and 6 reports probit estimates while the other columns report OLS estimates.

Table C.1.17: Effect of Digital Adoption on Firms' Outcome: PSM Balancing

Dependent Variables:	FixedAssets	Employment	Innov.(Share)	Exporter	Productivity Growth	Valueadded Growth
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Digital	-0.005	-0.009	-0.001	-0.004	-0.013	-0.011
	(0.040)	(0.026)	(0.006)	(0.009)	(0.009)	(0.009)
Fit statistics						
Observations	11,215	11,215	11,215	11,215	11,215	11,215
R^2	0.000	0.000	0.000	0.000	0.000	0.000

Figure C.1.1: Distribution of Propensity Scores



Note. Panel (a) depicts the distribution of propensity scores before matching while Panel (b) presents the propensity score distribution after matching.