**Shielding or Stifling? How Policies Restricting Foreign Acquisitions of Domestic Technologies Affect U.S. Entrepreneurial Innovation**

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**Abstract**
To achieve technological leadership, governments increasingly restrict foreign investments and acquisitions in critical domestic technologies. However, for domestic technology entrepreneurs relying on foreign funding as an exit strategy, such policies create uncertainty, reducing the market value of targeted technologies and discouraging their development. We examine this hypothesis using the impact of the blockage of foreign acquisitions of U.S firms by the Committee on Foreign Investment in the United States (CFIUS). We find that U.S. entrepreneurial firms within the same sector where CFIUS blocked foreign acquisition deals—including firms that did not directly experience such blockages themselves—experienced a significant decline of 18.13%, in their overall patented innovation output. This decline was most pronounced (25.79%) in the technological domains of the focal firm's core competence—the technological classes where the firm had previously focused its patented innovations efforts. The quality of patented innovations, proxied by their forward citations, also declined. Furthermore, these firms altered their technological trajectory, shifting away from their core competencies and entering new technological domains. However, the decline in quality of innovation within their prior core technological domain was *not* immediately accompanied by an increase in quality of innovation within their newly entered domains. Therefore, the costs of screening and restricting foreign acquisitions extend beyond the directly blocked firms and include two additional impacts: a reduction in overall innovation among industry peers, and the "switching costs" incurred by these firms as they attempt to shift to new technological domains where they are not immediately innovative.

**Keywords:** CFIUS blockage, innovation strategy and trajectory, regulatory uncertainty, technology acquisition

## 1. Introduction

Technology has become a key battleground in today's geopolitical landscape, particularly in critical, strategic sectors such as semiconductors, information technology, and biotechnology. Recognizing that acquiring foreign technologies through "technology acquisitions" can be a path to competitiveness (Ahuja and Katila 2001, Tsang 2002), countries increasingly protect their own critical technologies from foreign acquisitions and influence. A primary approach to gaining national security and long-term competitiveness is the employment of national security regulations to restrict foreign investors from acquiring domestic firms that are developing these technologies (Heath 2020, Heinemann 2012). For example, the Committee on Foreign Investment in the United States (CFIUS), an interagency committee authorized to review and, if necessary, block foreign investments in U.S. companies on grounds of national security, plays as such a role.

Accurate assessment of the costs of blocking foreign acquisitions of domestic technology firms is important. Recent studies show that such actions can directly impact the acquisition targets. Shi and Li (2023) suggest that restricting national foreign investment encourages managerial entrenchment and results in the inefficient allocation and use of R&D resources, hence decreasing innovation efficiency. Wajda and Aguilera (2021) find that national screening laws negatively influence R&D investment decisions; the effect of these laws varies with the quality of a country's governance. However, we know little about two key aspects of blocking foreign acquisitions: (a) how regulatory uncertainty caused by these blockages affects the broader group of technology firms within the same sector—particularly those that have not proposed foreign acquisitions and those whose propositions have not yet been blocked, and (b) how these firms' specific technologies and quality of innovation are affected beyond their previously studied, overall R&D investments.

There is reason to believe that this effect reshapes the broader technology market. Acquisition by a large firm is a primary exit strategy for entrepreneurial firms, particularly in high-tech sectors (Gilbert et al. 2006, Plummer et al. 2016). Blocking foreign acquisitions limits funding opportunities and reduces exit options in the affected technology domain; this presumably diminishes the relative value of developing that technology and thus threatens to ultimately alter the technological trajectory. If this is the case, then the impact on a broader range of entrepreneurial firms within affected sectors—even those not directly targeted—should be fully evaluated. This knowledge would help technology entrepreneurs and firms assess potential political risks and enable policymakers to evaluate this policy more comprehensively. Despite the importance of such needs, research has been limited research on how foreign-acquisition restrictions affect the broader set of peer firms within the affected sectors and on the trajectory of the entrepreneurial firms' innovation other than a change in volume.

We address this important research gap. Specifically, we investigate how blockage of foreign investors' acquisitions of U.S. firms by the Committee on Foreign Investment in the United States (CFIUS) affects the innovation outcomes of U.S. entrepreneurial firms operating within the same sectors as the blocked firms. The CFIUS review process is confidential and ambiguous, but news reports on blocked transactions serve as credible signals to the market that associated sectors are considered sensitive and subject to heightened CFIUS scrutiny. This increase in uncertainty limits the exit options for entrepreneurial firms. We predict that, following the news of a blockage, there will be a decline in the value that a domestic firm expects to capture from developing technology within the same sector. We also predict this will lead to a reduction in the firm's overall innovation output in that domain. Furthermore, we posit that following CFIUS's first instance of foreign-acquisition blockage within the sector, entrepreneurial firms in the that sector will reduce both the quantity and quality of innovation in their core technology areas. Instead, these firms will shift their innovation activities from the affected technology domains to technology domains that were previously less explored.

To test our predictions, we construct a longitudinal dataset of U.S. entrepreneurial firms and combine it with a comprehensive dataset of carefully hand-collected cases that CFIUS blocked from 2008 through 2017. Due to the confidential nature of the CFIUS review process, the blockage is typically sudden and unanticipated by the market. Therefore, we consider the news of blocked transactions to be a plausibly exogenous shock to the market. We employ a staggered difference-in-differences (DID) methodology to compare the innovation behavior of entrepreneurial firms in affected sectors before and after the news of the first incident of CFIUS blockage in their sectors.

Our findings reveal that news of an acquisition blocked by CFIUS led to 18.26% fewer patented innovations by entrepreneurial firms in the affected sectors, an effect that continued about three years after the blockage. This reduction is driven mainly by a decline of 25.75% in patents in these firms' core technology competencies—the technology classes where they had previously concentrated their patented innovation efforts. Importantly, we observe a decline in forward-citation-weighted patents in their core competence domains, indicating a drop in the quality of innovation in these areas. Meanwhile, these firms increased their patented innovation output in non-core technology domains that they had previously explored to a lesser extent. Because strategic adjustment is costly, the quality of innovation within the non-core technological domains, proxied by forward-citation-weighted patents, did not immediately increase. Finally, we find that the affected firms changed their innovation trajectory and shifted away from their prior areas of core competence, as proxied by a decline in backward self-citations in those domains (e.g., Huang et al. 2024).

Our study makes several contributions. This study contributes to the growing literature on how regulatory uncertainty affects firms' innovation. Beyond the common focus on affected firms' investments, particularly in tangible assets (Bernanke 1983, Bloom et al. 2007, Gulen and Ion 2015), we focus on innovation outcomes. In three ways we extend research on how policy uncertainty shapes innovation (Bhattacharya et al. 2017, Cong and Howell 2021). First, in examining not only the firms directly affected by these policies but also their peers in the affected sectors, we highlight a broader impact of regulatory uncertainty. Second, previous work on investment-related regulation and firm innovation has focused mostly on innovation quantities (e.g., Atanassov 2013, Shi and Li 2023). We analyze changes in citation patterns and shifts in technological domains, examining innovation quality and trajectory to capture the effects on innovation over a longer term and beyond sheer volume. Third, we examine shifts in technology trajectory by analyzing whether and how firms move away from their previous core domain into new domains where they have less established expertise. Collectively, these outcomes are important to understanding the changing competitive landscape and dynamics for affected firms and industries.

Existing research on the screening of foreign investment primarily adopts agency theory, viewing it as a means of increasing antitakeover protections (Shi and Li 2023, Wajda and Aguilera 2021). This perspective, however, overlooks how such regulations tilt the market by reducing the value that entrepreneurial technology firms expect to capture from developing the affected technology relative to other technologies. For entrepreneurial firms, which are typically smaller and less hierarchical, problems of agency may be less pronounced (Arthurs and Busenitz 2003, Garg 2020), but the value of acquisition as an exit option is paramount. Foreign-investment screening influences innovation outcomes via a new mechanism: altering the valuation of technology markets. Our study thus complements the agency perspective.

Lastly, despite a global trend toward tightening foreign-investment restrictions, few studies have examined the impact of restrictions on innovation by domestic entrepreneurial firms. We show that the CFIUS blockages also negatively affected entrepreneurial firms not directly involved in the blocked deals. For these firms, both the volume and quality of innovation decreased, and they incurred costs from shifting from their core competencies to new technological areas they had previously explored less. That is, the decline in quality, as reflected in citations to patents within their original technology domains, was not matched by an immediate rise in the quality of patents in newly explored areas. The costs of foreign-investment screening in terms of the innovation of domestic entrepreneurial firms are thus both multifaceted and significant; they should be key considerations in evaluating these policy instruments.

## 2. CFIUS Blockage of Foreign Acquisitions and Domestic Entrepreneurial Innovation

### 2.1 CFIUS: Function and Decision Process

CFIUS is an interagency committee authorized to review and block foreign investments in U.S. companies on grounds of national security. Established in 1975 through an executive order, CFIUS was initially established to protect the United States against possible threats from foreign takeovers of U.S. firms. For several decades after its establishment, the political uncertainty surrounding foreign investments remained relatively low (Byrne 2006).

In recent years, however, growing concern about potential leakage of sensitive technology through foreign ownership has driven reforms that have greatly expanded CFIUS's authority. Two particular reforms have augmented this authority significantly: the Foreign Investment and National Security Act of 2007

(FINSA) and the Foreign Investment Risk Review Modernization Act of 2018 (FIRRMA). FINSA's introduction had a significant effect on foreign-investment deals beyond merely increasing regulatory intensity (Rose 2015) as it empowered CFIUS to investigate foreign-investment transactions for any effect they might have on national security and to recommend to the president that deals be blocked. This reform led to more political uncertainty, scrutiny of foreign investors, and more congressional involvement in approving certain foreign investments (Calluzzo et al. 2017). As a result, by 2016 the number of cases investigated by CFIUS had increased sharply to 172 from just one in 2007 (CFIUS 2019). In 2018 FIRRMA further expanded CFIUS's scope and authority, authorizing it to review not only controlling investments but also certain non-controlling, non-passive investments and real estate transactions involving foreign parties in U.S. businesses. As a result, CFIUS now plays a critical role in regulating foreign investments and acquisitions in the United States and has become increasingly influential globally (Connell and Huang 2014). For this study, our observation period starts in 2008, one year after the enactment of FINSA and extends through 2017, one year before FIMMRA's implementation. This observation period provides a stable policy environment for investigating  CFIUS's impact.

CFIUS's regulatory procedure encompasses four stages: (i) Firms engaged in proposed foreign investments have the option to voluntarily notify CFIUS of their transactions. Even if they opt not to do so, however, they may still be required to submit a notice. (ii) Upon notice that the process has been completed, CFIUS will conduct an initial review lasting no more than 30 days to preliminarily assess the national security threat associated with the proposed transactions. (iii) If CFIUS determines that a transaction has potential national security risks, it will launch a more thorough investigation of no longer than 45 days. In this stage, CFIUS is authorized to mitigate national security concerns that emerged during the process. Specifically, CFIUS can negotiate, enter into, impose, and enforce "any agreement or condition with any party to the covered transaction in order to mitigate any risks to the national security of the U.S. that arises as a result of the covered transaction".[1] (iv) If the parties to the transaction and CFIUS cannot reach consensus on mitigations, CFIUS can recommend the pending transaction to the president for a final

[1] 50 U.S.C.  4565(l)(3)(A)(i)(2018), specifically clause (i).

decision, which must be announced within 15 days of the end of investigation. This flow is summarized in Appendix 1.

Prior to FIMMRA, CFIUS had authority to review all foreign investments leading to control of U.S. firms. FIMMRA extended this authority even to non-controlling investments in U.S. firms. It is important to note that even though firms may choose not to submit a notice, CFIUS still has the authority to initiate a review and investigation process targeted at the transaction. As a result, all foreign investments involving U.S. firms fall within the scope of CFIUS screening. According to CFIUS's report to Congress for 2021, "CFIUS utilized various methods to identify non-notified/non-declared transactions in 2021 including interagency referrals, tips from the public, media reports, commercial databases, and congressional notifications" (CFIUS 2021).

Based on its review, CFIUS can block proposed transactions directly or indirectly. After the review and investigation are completed, CFIUS may refer the transaction to the president, who has the authority to block it directly. Alternatively, during the investigation stage, the proposed parties may "voluntarily" withdraw the notice and terminate the transaction. This typically occurs when CFIUS and concerned firms do not reach consensus on mitigation measures to address identified risks. Although the president holds the power for the final decision, it is relatively rare for transactions to be blocked by this means, as most firms tend to terminate or modify their deals before reaching the presidential-review stage.

**2.2 Regulatory Uncertainty of CFIUS and Exogenous Shocks to Affected Sectors**

The CFIUS review process has two key features that increase regulatory uncertainty. First, the jurisdictional range is ambiguous (Connell and Huang 2014, Lai 2021, Shi et al. 2021). While CFIUS is authorized to review transactions that threaten national security, the term "national security" does not have an explicit definition. Esplugues (2018) notes that, "no definition of national security has ever been provided and no clear guidance on how it should be understood has been given. ... It seems to have been deliberately left open to interpretation by the executive ... (and) ... the final understanding of what constitutes a threat to national security is largely left to executive discretion." This intentional ambiguity in the range of power granted to CFIUS gives it considerable discretion in interpretation, as it "determines the scope of its own jurisdiction and is afforded significant deference by the courts" (Latham & Wilkins 2020).

As a result, this discretion in interpretation leads room for different interpretations, which are largely influenced by political concerns and changes in regulatory focus. Consequently, the seeming lack of transparency and coherence regarding regulatory criteria contributes to the uncertainty. For firms involved in foreign investments, the review process resembles a “black box,” in which firms can only know the outcome after CFIUS has intervened. Therefore, it is difficult for firms to anticipate a potential blockage because their understanding of the jurisdictional scope is limited.

Even in the absence of clear criteria, firms might attempt to use precedent as a reliable guide to infer the decision of a CFIUS investigation. However, confidentiality—another key feature of CFIUS’s review—makes it difficult to utilize precedents. The CFIUS process mandates confidentiality in all cases. According to the U.S. Department of the Treasury: “Section 721 of the Defense Production Act of 1950, … prohibits the Committee from publicly disclosing any information filed with the Committee, subject to limited exceptions. Information and documentary material filed with the Committee are also exempt from disclosure under the Freedom of Information Act, 5 USC. § 552.” As a result, the cases reviewed by CFIUS are not publicly disclosed except for presidential blocking orders, which are made public. The non-disclosure nature of CFIUS reviews leaves investors and businesses with limited knowledge of precedents to which they might refer, making it more difficult to anticipate how CFIUS might respond to their transactions.

While any transaction involving foreign parties can be subject to CFIUS review, it is widely acknowledged that CFIUS intervention is more likely in transactions involving critical or sensitive technologies, such as semiconductors and telecommunications. In contrast, certain industries—such as art, entertainment and recreation—are considered less critical and raise few concerns about national security. Due to the intentionally ambiguous nature of the review process, however, the criteria for determining priorities among critical technologies—which are simply labeled “national security” concerns—are affected greatly by political concerns and by shifts in strategy that change over time.

The coverage of “critical technologies” has also evolved over time (Eichenauer and Wang 2024). In other words, the sectors regarded as involving “critical technologies” may not always receive the same level of scrutiny, and firms operating in these sectors may experience varying levels of regulatory uncertainty. For example, CFIUS has focused increasingly on foreign access to personal data (Boylan and Fisher 2022). If a proposed transaction could grant a foreign entity direct access to such data, especially when the industries involved contain large volumes of sensitive information, CFIUS is likely to conduct a more thorough review.

Experts suggest that the uncertainty introduced by such investment regulations will decrease over time, but case-specific uncertainty will remain longer (Eichenauer and Wang 2024). Given these circumstances, news released to the public about a specific case can serve as a plausibly exogenous shock to the relevant industries. Blockage events are typically sudden and largely unanticipated by the market. The parties involved—not to mention the market at large—may have limited knowledge of the ongoing CFIUS process. Consequently, public announcements serve as the sole source of information about blockage events and are typically disclosed by the parties concerned only after a decision has been made. The persistent confidentiality and ambiguity prevent the market from anticipating whether and when proposed transactions will be blocked. Furthermore, the news acts as a negative signal to market participants in transaction-related industries. For those in affected sectors, a CFIUS blockage signals heightens regulatory scrutiny and the likelihood of similarly rigorous reviews for future foreign-investment transactions. As a result, firms must adapt their strategies to account for increased uncertainty.

**2.3 Hypotheses on Firms' Innovation Outcomes**

Policy uncertainty can depress firms' investments (Bernanke 1983) and particularly threatens innovation activities (Baker et al. 2016, Bloom et al. 2007, Gulen and Ion 2015) because these activities are often associated with new approaches and risky methods that require substantial investments in intangible assets (Ferreira et al. 2014, Holmstrom 1989, Manso 2011). Firms tend to hold back on innovation investments in uncertain political environments such as political elections (Bhattacharya et al. 2017) or when financial regulatory activity indicates suspicion of initial public offering (IPO) (Cong and Howell 2021).

The release of news of a CFIUS blockage signals firms in the affected sectors that their industry is under increased regulatory scrutiny related to the national security and indicates that regulatory intervention in future transactions is more likely. The news generates anticipation of additional direct transaction costs—

such as filing fees and costs associated with mitigation agreements—to ensure regulatory compliance (Klemencic 2022, Tipler 2014, Zaring 2010). Also, foreign-investment screening tools restrict access to critical funding sources through both direct and indirect channels. The "CFIUS discount" phenomenon, wherein foreign investors devalue firms in sensitive sectors, reflects the increased risks involved (Eichenauer and Wang 2024, Westbrook 2018). Furthermore, CFIUS blockages create a deterrent effect, shrinking the pool of potential foreign investors and exacerbating capital constraints on entrepreneurial firms. In addition, the delays introduced by the review process add timing uncertainty, a significant challenge for high-growth entrepreneurial firms reliant on rapid funding cycles (Gans et al. 2008). Taken together, these uncertainties reduce the attractiveness of the affected sectors, leading firms to scale back their innovation efforts within these sectors. Therefore, we hypothesize:

***Hypothesis 1 (H1):*** *After CFIUS blocks a foreign acquisition, domestic entrepreneurial firms in the same sector as the blocked firm will reduce their overall innovation output.*

We postulate that firms will reduce their overall innovation activity, but their approach to resource allocation across different technological domains may vary. Under conditions of uncertainty, firms reevaluate their investment allocation and may choose to redirect resources away from the affected domains and toward alternative technological domains. This shift occurs because, as uncertainty and costs associated with a firm's core competencies rise, the firm expects its returns from innovation in that domain to decline (Long et al. 2020, Roberts and Weitzman 1981). Firms respond to rising uncertainty by delaying commitments into that particular technological area and by maintaining their flexibility to adapt to a new environment (Huchzermeier and Loch 2001). Consequently, firms may begin reducing their innovation efforts in their domains of core competence, moving instead to less affected technological domains—even if they have not yet developed technology expertise in those areas. This strategic reallocation of resources is thus reflected in less innovation output within the firms' core technological domains. Therefore, we hypothesize:

***Hypothesis 2 (H2):*** *After CFIUS blocks a foreign acquisition, the quantity of innovations in the core technological competency domains of domestic entrepreneurial firms in the same sector as the blocked firm will decrease.*

Following a CFIUS blockage, a shift in focus away from their core technological competencies leaves firms with fewer resources available to sustain their previous level of innovation quality in those core areas. Novel and high-quality innovations typically take longer to develop, carry higher risks, and have greater rates of failure compared with more general technologies (Fleming 2001, 2007). Moreover, sustained investment and continuous engagement in a specific technological domain are critical for accumulating domain-specific knowledge and expertise (Cohen and Levinthal 1990). This accumulated knowledge, combined with experience working in the same domain, enhances a firm's ability to identify promising opportunities, refine ideas, and overcome development challenges—all of which lead to higher quality innovations (Zhou and Li 2012, Zahra and George 2002). Therefore, when firms divert resources from the core domains of their technological competence, they not only reduce the quantity of innovation but also impair its quality, as the absence of sustained focus disrupts the iterative process of learning and improvement that drives breakthroughs in specialized fields.

***Hypothesis 3 (H3):*** *After CFIUS blocks a foreign acquisition, the quality of innovation in the core technological competency domains of domestic entrepreneurial firms in the same sector as the blocked firm will decrease.*

Where then should firms reallocate the resources that would have been invested in their core competencies if not for the regulatory uncertainty? As these are technology entrepreneurs, we argue that they are likely to continue engaging in the business of developing technologies rather than in diversifying into entirely unrelated industries. Their expertise, resources, and networks are deeply rooted in the technology sector, making it more feasible and strategically sound for them to explore adjacent or emerging tech domains rather than pivot to industries outside their knowledge base. Any other technology domain to which they shift their attention, outside of their previously established core domain, is considered a non-core domain. Developing technologies in non-core domains provides firms with potential pathways to innovate in areas with fewer regulatory barriers to foreign investment and collaboration. This strategic shift enables firms to remain competitive and to seek new growth opportunities while mitigating risks associated with heightened regulatory scrutiny in their core areas. Thus, we generate the following hypothesis:

***Hypothesis 4 (H4):*** *After CFIUS blocks a foreign acquisition, the quantity of innovation in new technological domains outside the core competencies of domestic entrepreneurial firms in the same sector as the blocked firm will increase.*

## 3. Methods

### 3.1 Data and Sample

The data sets used in this study were collected from several sources. First, we collected the event-level data on CFIUS blockages from the Factiva database, a major newspaper database (Flammer 2013). We identified two types of transactions as blocked, either directly or indirectly: (i) proposed transactions that were blocked by the president, and (ii) those withdrawn during the CFIUS investigation process. We regard these transactions as blockages resulting from CFIUS intervention. To identify relevant cases, we initiated a keyword-related, comprehensive search on Factiva, covering all publicly released articles in English from during a ten-year time window from 2008 through2017.[2] We supplemented the Factiva database by searching major web engines to search for relevant news. From the search results, we manually collected the names of the parties involved in transactions and recorded the date when news about this event was first released. These event-level data were manually cross-checked and cross-referenced to news articles from other media sources and industry research reports.

We note three critical features of this context. First, because a sector could be affected by more than one blocked case, our DID estimation focuses only on the first blockage in that sector by CFIUS. Second, when news of a specific blockage case is first released, different media follow up and continue to report the case over time. Given the recurring news reports of a specific blockage, we document only the date of the earliest event-related news; we consider this date to be the occurrence of the shock. Third, considering the time of shock to be the year following the earliest release of news about a blockage. This approach captures the lag in strategic adjustments by market participants and provides a more accurate measurement of the impact of the announcement on innovation outcomes.

[2] We conduct a search of CFIUS-blocked individual transactions by relevant keywords that include "CFIUS," "block," "blockage," "abandon," "terminate," "prevent," "prevent," "withdraw," etc.

According to annual reports by CFIUS, during the observation period 2008 through 2017 there were 1,334 notices to transactions, of which 84 were investigated and 204 were withdrawn during the review or investigation processes. Given the characteristics of CFIUS operations, we were unable to identify precisely all unreleased blockages or to acquire their details. Therefore, we utilized public news reports to search for released blockage. Using this procedure, we identified twelve deals that were blocked by CFIUS during the observation period. Detailed information about each transaction was collected, including the year of the earliest news release, the trading business sector, potential foreign investors, and local investees. Table A1 in the Appendix provides detailed information about the blocked transactions.

Second, to measure the innovation activities and outputs of firms in the sample, we obtained patent data from the U.S. Patent and Trademark Office (USPTO) to provide a proxy for the innovation output of targeted firms. This dataset contains comprehensive records of patents granted by USPTO since 1976, and includes detailed information on dates of patent publication and application, technology classes, and assignees as well as backward and forward citations, among other important patent-level attributes.

Third, we collected data on firm attributes from the Refinitiv VentureXpert database provided by Thomson Economics (formerly Thomson Reuters VentureXpert and Venture Economics). This database provides accurate and comprehensive information on entrepreneurial firms (Kovner and Lerner 2015), and is widely used in venture-related and entrepreneurship research. From this database, we extracted all VC-backed entrepreneurial firms that were founded in the United States. To ensure that the sample consisted only of young and pre-IPO firms, we excluded firms that had completed their IPO before the start of the observation period and firms that were more than ten years old at the start of the period. Then we constructed our research sample by selecting all firms operating in critical sectors as identified in the 2008 CFIUS annual report. Thus, both our treatment and control groups are firms within critical sectors and both groups exclude firms in less critical industries like arts and entertainment, which are unlikely to pose national security concerns. As a result, our sample includes a ten-year observation period with 2,118 VC-backed entrepreneurial firms. The geographic distribution of these entrepreneurial firms is shown in Appendix 3.

We matched these datasets using the following four steps. First, the blockage news was matched with associated U.S. firms by manually checking the news content to identify the entities associated with the blocked deals/events (described above) and the dyads of proposed investors and U.S. firms involved as proposed investees.

Second, to identify the sectors affected by blockage, we matched the proposed industry classification of U.S. investees according to the North American Industry Classification System (NAICS) at the three-digit level based on the primary industries of the intended investees. Using descriptions provided in the news, we identified each investee's primary business class by searching for the business's keywords in the NAICS classification list. We selected three-digit NAICS codes that best describe the investees' business class. Because there are 99 three-digit NAICS codes (compared with 20 two-digit codes and 311 four-digit codes, we chose the three-digit codes as neither too broad nor too narrow to impose influence. A firm's primary business may span several sectors, so we considered only the business line included in the proposed transaction. However, the business line of a proposed transaction may match with multiple NAICS codes. Considering that a blocked transaction may affect firms operating in all relevant sectors, we included all related NAICS codes that matched each case. As a result, 14 unique three-digit NACIS codes were identified as the sectors affected by the "shock."

Third, to obtain detailed firm-level information, we matched targeted NAICS codes with detailed information from the Refinitiv VentureXpert database for U.S. entrepreneurial firms affected by the blockage. We also identified all U.S. entrepreneurial firms from this database that were not affected by the blockage.

Lastly, using information from the USPTO database and patents, we matched these entrepreneurial firms with the patents for which they had applied and that were eventually granted. Our matching process follows the procedure applied in previous studies (Bernstein et al. 2016, Ma 2020). We then calculated the number of patents and citation-weighted patents, and the self-citations ratio at the firm-year level. In summary, we constructed a panel dataset with all entrepreneurial firms included in the Refinitiv VentureXpert dataset with detailed firm-level information and attributes, their exposure to CFIUS blockage shock, and their patent data from 2008 through 2017. Figure 1 summarizes our data construction process.[3]

[INSERT FIGURE 1 HERE]

[3] Details of the matching process are available upon request.

### 3.2 Variables

We construct the following dependent variables to capture the innovation outcomes of focal firms . The quantity of the firm's patented innovations is measured by *number of patents*, defined as the total number of patent applications by the focal firm in the given year that were eventually granted by the USPTO. The quality of the firm's patented innovations is measured by *citation-weighted patents*, defined as the total number of forward citations of the firm's patents in a given year divided by the number of the firm's patent applications (eventually granted) filed in that year (e.g., Aggarwal and Hsu 2014, Vakili 2016).

We categorize the firm's patents into those that belong to the firm's core patent classes and those that fall outside these core areas (i.e., non-core patent classes). This categorization allows us to better understand how a firm's core areas (versus non-core areas) of technological competencies are differentially impacted by foreign-investment screening policies. To ascertain a firm's core patent classes, we follow Huang et al. (2024) and count the number of patents for which the firm applied in each patent class (Cooperative Patent Classification or CPC) over the past five years and calculate its proportion to the total number of patents for which the firm applied. The patent class with the greatest proportion is defined as the core class. If a patent class is not the firm's core patent class, it is considered to be a non-core patent class. Based on the categorization of core and non-core patent classes, we construct the following dependent variables: *patents in core classes*, *patents in non-core classes*, *citation-weighted patents in core classes*, and *citation-weighted patents in non-core classes.*

To examine firms' trajectories of technological diversification, we further categorize the non-core technological classes into "first-entry" classes—that is, patent classes that have appeared for the first time in the focal firm's patent portfolio since its founding—and "repeated" classes—that is, patent classes that have appeared more than once in the focal firm's patent portfolio since its founding. Patents in non-core and first-entry classes represent the firm's efforts to explore and enter new technological fields outside their core competencies. Patents in non-core and repeated classes represent the firm's continued efforts in more familiar technological fields outside their core competencies. Based on this distinction, we construct the following variables: *patents in non-core and first-entry classes*, *patents in non-core and repeated classes,* *citation-weighted patents in non-core and first-entry classes*, and *citation-weighted patents in non-core and repeated classes.*

The main explanatory/independent variable is *post-blockage*. We regard a firm as treated if its industries, as reflected by its three-digit NAICS code, were affected in a CFIUS blockage case. For firms in the treatment group, the indicator variable is coded as 1 starting in the year after the occurrence of the blockage event in that sector, and 0 otherwise. For non-treated firms in the control group, *post-blockage* is always coded as 0. In this study, *post-blockage* is our main DID variable of interest.

We include the following control variables in our models at the firm level. Consistent with prior studies, we control for *firm age*, which affects the performance of entrepreneurial firms in terms of growth. We also control for *cumulative patents*, defined as the cumulative number of patented innovation outputs produced by the firm in the most recent three years. This variable provides a proxy for the cumulative innovation capability of the focal firm. To control for whether the focal firm became public firm through an IPO that would affect the firm's resources and hence its performance, we include the indicator variable, *IPO indicator* in our models. In all the regression models, we include firm fixed effects and year fixed effects to control for any potential underlying heterogeneity across firms and years respectively. Table 1 provides the variable definitions and summary statistics of the firm-year panel dataset and Table 2 shows the pairwise correlations for these variables.

[INSERT TABLE 1 AND TABLE 2 HERE]

**3.3 Estimation Strategy**

In our empirical analyses, we focus on the effect of CFIUS blockage on firms in related industries. We consider this a plausibly exogeneous event and perform a staggered DID estimation to examine the effects of CFIUS blockage on the difference in innovation outcomes between the firms in the treatment group and those in the control group, both before and after the blockage. To do this, we use our main DID variable of interest, *post-blockage*, and assess its coefficient in the regression models. This estimation strategy is commonly used to examine policy implementation at different times for firms in a treatment group (Jia et al. 2019, Huang et al. 2024, Tsolmon 2024). Our treatment group consists of firms within blockage-related industries, while our control group consists of firms operating in industries that have never been affected by blockage. We adopt a propensity score matching (PSM) approach to match the treatment group of firms to a comparable control group of entrepreneurial firms.[4] The matched firms in the control group belong to CFIUS-listed critical industries that were not affected by the shock from blockages during our observation period. The match is based on key attributes of entrepreneurial firms; these include firm age, total funds received, and IPO status by year. As a robustness check, we use the coarsened exact matching (CEM) procedure and obtain similar and consistent results.

Our main dependent variables, *number of patents* and *citation-weighted patents*, are count variables that take on non-negative values. They are highly right-skewed as some firm-year observations have a large number of patents. Hence, we use a nonlinear regression approach to avoid heteroskedastic, non-normal residuals (Hausman et al. 1984). Specifically, we use quasi-maximum likelihood (QML) estimates based on the fixed-effects Poisson regression model (Hausman et al. 1984, Jia et al. 2019). The fixed-effects Poisson estimator produces consistent estimates of the parameters in an unobserved component multiplicative panel data model under general conditions and provides a consistent estimate of the conditional mean function even if the variances are misspecified (Wooldridge 1999). We perform baseline regression models that include only the main explanatory variables to ascertain the effects of key explanatory variables (and to ensure robustness) and full models that include all the control variables.

In all models, we include robust standard errors to account for possible heteroskedasticity and a lack of normality in the error terms (Greene 2004). We also cluster the standard errors by firms to adjust for potential non-independence across same-firm observations over time. All regression models include firm fixed effects and year fixed effects.

## 4. Results

### 4.1 Effects on Firms' Overall Innovation

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[4] We employ the nearest-neighbor matching approach, selecting two neighbors for each treated unit to improve the robustness of our matched sample. In addition, we perform robustness checks using the caliper-matching approach with calipers set at 0.1, 0.05, and 0.01 to test progressively narrower thresholds. These calipers are sufficiently tight to produce close matches for efficient estimation. Across these different caliper sizes, the results remain similar. The set of results demonstrates that our findings are robust to variations in caliper width and in matching methods.

We start our analyses by examining whether entrepreneurial firms reduce their overall innovation output after the first time their industries are affected by CFIUS's blockage. Table 3 reports the results from our fixed-effects Poisson regression models for the DID estimations of overall patented innovations and for those in the firms' core areas of technological competencies (patents in core classes). The dependent variable in Models 3-1 and 3-2 is the *number of patents*. Model 3-1 is the baseline model without any time-variant control variables. Model 3-2, our main (and preferred) model, controls for *cumulative patents*, *firm age*, and *IPO indicator*. Both the baseline and main models show that *post-blockage* is associated with a significant ($p < 0.01$) decrease in the firm's total number of patents; the decrease is 25.74% in Model 3-1 and 18.26% in Model 3-2. These results support H1. That is, after CFIUS blocked a proposed transaction of a U.S. firm, entrepreneurial firms in targeted sectors substantially reduced the overall quantity of their patented innovations.

[INSERT TABLE 3 HERE]

We conduct parallel trend tests to examine the effects of CFIUS blockages on the number of patents produced by targeted firms, as shown in Figure 2. Prior to the exogenous event caused by the CFIUS blockage, there are no significant pre-trends in either graph. However, after the blockage event, the number of patents shows a significant decline. These observed trends align with our hypotheses and further corroborate the conclusion that firms in industries targeted by CFIUS blockages reduced their patent production.

[INSERT FIGURE 2 HERE]

**4.2 Effects on Firms' Core Areas of Technological Competencies**

In H2 and H3, we predicted that the effects of the CFIUS blockage were not uniform across a firm's different technological areas. To further investigate these differential effects, we split the patents into subsamples based on whether they belonged to the firm's core or non-core technological classes and examined their respective responses to the blockage. Table 4 reports the results from estimating the effect of *post-blockage* on the patents in firms' core competence areas. Models 4-1 and 4-2 use *patents in core classes* as the dependent variable, where Model 4-1 is the baseline model and Model 4-2 is the full model. The results show that the CFIUS blockage led to a significant ($p<0.01$) reduction in the *patents in core* *classes*; this reduction was 30.06 % in the baseline model and 25.75% in the full model. These results are consistent with H2, indicating a pronounced decline in firms' patented innovations in their core technological areas.

In Models 4-3 and 4-4, the dependent variables are *citation-weighted patents in core classes*. The coefficients are both significant ($p$<0.05) and negative, suggesting the blockage is associated with reductions—23.91% in the baseline model and 23.13% in the main model—in the quality-adjusted output of patents in the core technology classes. These results indicate that CFIUS blockage diminishes the quality of patents in terms of their citations, supporting H3. In summary, the blockage has a negative impact on innovation performance in the areas of core competence of affected firms.

Thus far, we have examined the effects on overall innovation and core innovation separately. By comparing Table 3 (overall innovation) and Table 4 (core areas of technological competence), we observe how CFIUS blockage affects firms' overall innovation differently from its effect on their core areas of competence. While both the number of patents overall and the number of patents in core technology areas have declined after the blockage, the negative impact on core technology areas was disproportionately high. Specifically, when comparing the results from Model 3-2 (*number of patents*) with those in Model 4-2 (patents in core classes), we find that CFIUS blockage had a greater negative effect on the quantity of firms' innovation in their core technological classes (25.75%) than on the quantity of their innovation overall (18.26%).

Taken together, these results indicate that the negative impact of the blockage on innovation quantity is more concentrated in the core technological areas of firms in the same industry as the affected firm. The larger reduction in core patenting relative to overall patenting highlights the important strategic shift among firms as they not only reduce the amount of innovation but also reduce their focus on the areas where they previously held a competitive advantage.

[INSERT TABLE 4 HERE]

We conduct parallel trend tests to examine the effects of the CFIUS blockage on targeted firms' *patents in core areas* and report the results in Figure 3. Prior to the exogenous event, the CFIUS blockage, there are no significant pre-trends in either graph. After the blockage, however, the number of patents in core classes declined significantly. These observed trends are consistent with our hypotheses. The results suggest that firms in industries targeted by CFIUS blockage reduced their production after the event, as reflected in the fewer numbers of patents overall and of patents in core classes after the event.

[INSERT FIGURE 3 HERE]

### 4.3 Effects on Firms' Non-Core Areas of Technological Competence

To test the impact of CFIUS blockage on innovation in entrepreneurial firms' non-core areas of technological competence, we examine the effect on the quantity of patents and on the quality of firms' patents in non-core classes; the results are shown in Table 5. Model 5-1 reports the impact of blockage on the overall number of patents in areas outside firms' core competencies (i.e., in non-core classes); the result suggests that, in general, the effect of CFIUS blockage on these firms' quantity of innovation is limited.

[INSERT TABLE 5 HERE]

Next, we test H4, which predicts a positive effect on the quantity of innovation as affected firms shift into technological domains less associated with a blockage. We use the dependent variables, *patents in non-core and first-entry classes* and *patents in non-core and repeated classes*. Model 5-2 shows that blockage leads to a significant increase of 35.92% ($p<0.1$) in the quantity of patented innovation in new technological areas outside the firms' core competencies. In contrast, the coefficient of post-blockage in Model 5-3 is not significant, indicating the blockage does not have a significant effect on firms' innovation in more familiar technological areas outside their core competencies. Taken together, these results suggest that, following CFIUS blockage, firms tend to shift their innovative efforts away from their areas of core competence, particularly toward new technological areas outside this core; thus, these results support H4.

### 4.4 Post-hoc Analysis: Quality of Innovation in Non-Core Technological Domains

We have not theorized about changes to the quality of innovation in a firm's non-core technology domains. There are competing factors at play: On one hand, firms entering new areas may take time to reach the frontier, which can potentially delay the development of high-quality innovation. On the other hand, a strategic shift may lead to increased effort and resource allocation that enhance the likelihood of achieving novel innovations.

We empirically examine changes in the quality of innovation output in areas outside the firm's core technological competencies after blockages. We find that CFIUS blockage has no significant effects on *citation-weighted patents in non-core classes*, *citation-weighted patents in non-core and first-entry classes* and *citation-weighted patents in non-core and repeated classes*, as indicated in Models 6-1, 6-2, and 6-3, respectively. These results may reflect the countervailing effects discussed earlier.

[INSERT TABLE 6 HERE]

In summary, the results reported in Table 6 suggest that, when CFIUS blockage compels firms to shift their innovative efforts from their areas of core competence to new technological areas outside their core, these firms actively enter less explored areas. Consequently, these firms may experience an increase in the quantity of innovation within the newly entered fields. However, this shift does not correspond to a significant improvement in the quality of innovation in these new areas.

**4.5 Further Analysis: Technological Trajectory Shifts**

We predict and find support for a reduction in the quantity of innovation in areas of core technological competence following the CFIUS blockage (H2). We argue that this is likely due to firms shifting their innovation efforts away from their core competencies. If this is the case, the firms would reduce their reliance on, or build less upon, their past core competencies; this can be observed through a reduction in the backward self-citations of the firms' patents in their core patent classes. This reduction indicates that firms draw less upon their own patented technologies in their core areas of strength (Huang et al. 2024, Zhao 2006).

In other words, backward self-citations of patents in a firm's core classes suggest that the firm is building upon its existing expertise in these core technological areas. Specifically, a high proportion of self-citations of patents in these core classes shows that the firm is actively using and building upon its knowledge base in these areas to develop its future innovations. Conversely, when the firm cites fewer of its own past patents in these core areas, it suggests the newly developed patents are built less upon the firm's core technologies, indicating a likely shift away from the firm's prior core technologies. Therefore, as further support for H2, we predict and show that, after CFIUS blockage, firms in a targeted industry will draw less upon their prior areas of core technological competence.

To do this, we categorize the firms' patents into core and non-core patent classes and examine the backward self-citations of patents in these classes respectively. The proportion of backward self-citations is calculated by the proportion of the total number of self-citations that a firm has cited in all its patent applications (that were eventually granted) filed in a given year  to the total number of all citations (self or external) made in the firm's patent applications (that were eventually granted) filed in the same year. We then reconstruct the backward self-citations proportions using such self-citations in the firm's core and non-core patent classes respectively. We construct *backward self-citations in core classes, backward self-citations in non-core classes,* and overall *backward self-citations* (all classes)*,* as additional dependent variables*.* Following prior studies using backward citations as a dependent variable (Huang et al. 2024), we adopt the ordinary lease squares (OLS) regression model to measure the effects on backward self-citations.

Table 7 shows the results. In Models 7-1 and 7-2, the dependent variable is *backward self-citations in core classes*. In Model 7-2 with all the controls, we find a significant reduction of 0.26% ($p$<0.1) in the proportion of backward self-citations in core technology classes following CFIUS blockage. This decrease suggests a reduced reliance upon and likely shift away from firms' prior core technological competencies. In contrast, the effects on *backward self-citations in non-core classes* and *backward self-citations* (all patent classes) as shown in Models 7-3 and 7-4 respectively, are not significant.

[INSERT TABLE 7 HERE]

To ensure that our results in Table 7 on the proportion of backward self-citations are not driven by changes in citation patterns over time, we conduct a robustness check using the *number of backward self-citations* as an alternative dependent variable and report the results in Table A2 in the Appendix. In Models A2-2, A2-3, and A2-4, to control for differential effects due to a change in the total number of backward citations, we include *backward citations number* as an additional control variable. The results are largely consistent with those in Table 6.

Taken together, these results suggest that, following a CFIUS blockage, firms in targeted industries likely have changed their innovation trajectory and shifted away from their prior areas of core competence. These findings provide further insights into H2.

**4.6 Further Analysis: Duration of Effects**

We also examine the longer-term effect of CFIUS blockage. To do this, we lag the main explanatory variable, *post-blockage*, for one to six years. As shown in Tables A3 and A4 in the Appendix, the negative impacts on the overall number of patents and on patents in core classes are statistically significant for the first three lagged years and diminish afterward. The negative impact on the number of patents in core classes also shows a greater decline during the first three lagged years. These results suggest that the negative impact of the blockage on firms' innovation activities, including on their core technological competencies, persists beyond the immediate aftermath.

## 5. Discussion

Our study investigates how policy restrictions on foreign investments, specifically blockages by CFIUS, affect the innovation strategies, trajectories, and performance of entrepreneurial firms. The nature of CFIUS intervention in specific industries provides an ideal quasi-experimental setting in which to assess the effects of such regulatory interventions on firms operating in those industries. We find a significant and durable decline in the overall number of patented innovations of entrepreneurial firms operating in industries targeted by CFIUS blockages. The reduction is more pronounced in the number of patent applications in the firms' core areas of technological competence. Moreover, this blockage also elicits a strategic shift in firms' innovation efforts—from their areas of core competence to unexplored, new technological fields. However, while the quality of innovations in the firms' core areas of competence declines, this shift does not immediately result in the development of quality innovations in the new areas. Taken together, these results further support the idea that such investment screening tools may not only reduce the firms' overall innovation productivity but also may shift the firms' innovation trajectories.

Our study makes several theoretical contributions to the literature on innovation, regulatory uncertainty, and foreign-investment screening. First, it extends the growing body of research on how policy uncertainty impacts firms' innovation outcomes. It highlights the broader effects of regulatory uncertainty, not only on firms affected directly (e.g. Cong and Howell, 2021) but also on their peers within the same technological domain, impacting both the quantity and quality of their innovation. We go beyond the traditional focus on volume of innovation to analyze shifts in technological trajectories (Huang et al., 2024), capturing longer-term effects on firms' strategic choices and industry dynamics.

Second, this study contributes to the literature on foreign-investment screening by offering a novel perspective that complements the more dominant lens of agency theory. While prior research has primarily framed foreign-investment screening as a mechanism to address agency problems (Shi and Li 2023, Wajda and Aguilera 2021), we show how such regulations alter the relative value of different technological domains, tilting the innovation market for entrepreneurial firms.

Lastly, this study addresses a significant gap in the literature on the impact of foreign-investment restrictions on innovation by entrepreneurial firms. This impact is particularly relevant for smaller, less hierarchical firms for whom exit options through acquisitions are crucial. By highlighting how foreign-investment restrictions reshape technological trajectories and innovation quality, we provide a richer understanding of the trade-offs of such policies.

**5.1. Policy and Managerial Implications and Future Research**

The evidence from this study is consistent with the notion that heightened regulatory uncertainty can disrupt the corporate innovation process. Our findings not only add to the literature on the consequences of policy uncertainty but also identify important policy implications of such regulatory tools. Our results suggest that policymakers should be cognizant of the effects of policy instruments that restrict foreign acquisitions and investment in domestic firms and their critical technologies. Further, policymakers should seek to balance the need to protect national security with the potential costs to domestic innovation. Foreign-investment screening may be crucial to prevent rival countries from acquiring critical technologies, but it is also important to recognize its broader negative impact on the domestic innovation ecosystem, particularly for entrepreneurial firms; this ecosystem is a key driver of technological innovation and the economy. The unintended consequences of CFIUS blockages—a significant reduction in the quantity and quality of core technological innovations that also compels entrepreneurial firms to change their innovation trajectories—suggest that overly stringent or frequent interventions could undermine the critical technology sectors that they aim to protect and cultivate.

This study also generates important managerial implications. Our findings show that intensified geopolitical tensions and regulatory uncertainties can reduce the attractiveness of targeted technologies. Although shifting to new and less explored areas may offer new opportunities, it could diminish core technological competencies while new areas of competency are still underdeveloped. The effects of such uncertainty are even more salient in today's geopolitical climate. To maintain a firm's overall innovation capabilities, managers must carefully assess the trade-offs of strategic shifts and must balance resource allocation between core and emerging technological areas. Additionally, managers should evaluate their strategic options, identifying and prioritizing technological domains with fewer regulatory constraints as these areas present opportunities for growth and investment with fewer risks.

Future research can focus on conducting comparative global studies. While this study uses the lens of CFIUS to investigate the impact of foreign-investment restrictions in domestic firms in the United States, similar regulations have been implemented in other regions, such as the European Union. However, the extent to which these restrictions in different jurisdictions affect the innovation strategies and outcomes of domestic firms remains understudied. In addition, cross-national comparisons could provide valuable insights into how institutional and cultural factors influence firms' strategic responses to regulatory uncertainty.

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# Figures and Tables

**Figure 1. Data construction**

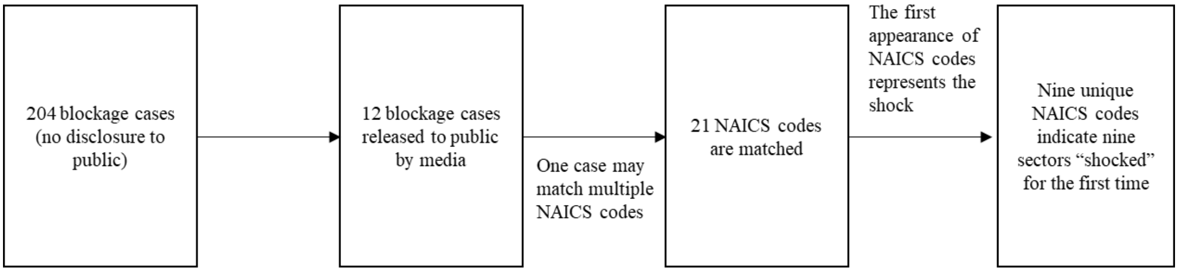



**Figure 2. Parallel trend test of all patents issued to the entrepreneurial firms**

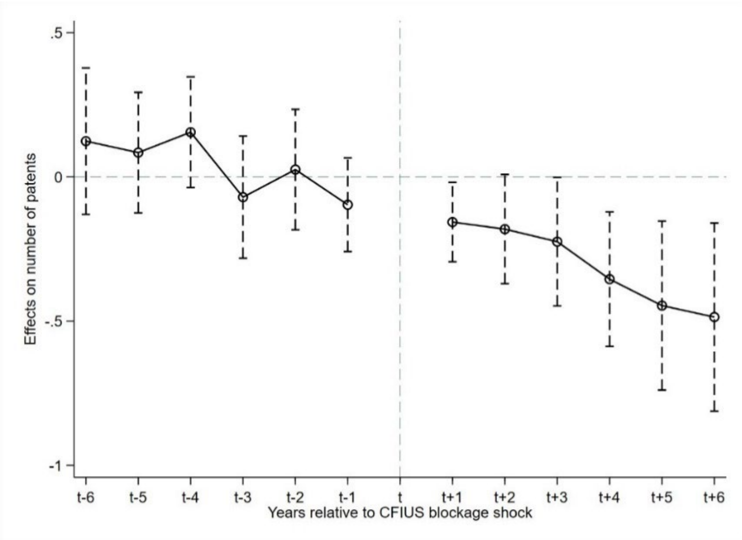



**Figure 3. Parallel trend test of patents in core classes issued to the entrepreneurial firms**

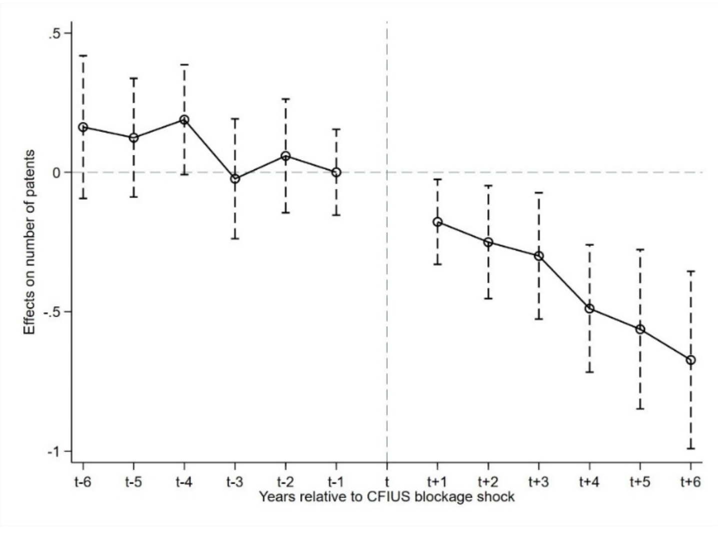


**Table 1. Variable definition and summary statistics**

| Variable | Definition | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| **Key dependent variables** | | | | | |
| Number of patents | The total number of all patent applications by the focal firm in the given year that were eventually granted by the USPTO. | 2.374 | 12.605 | 0 | 628 |
| Patents in core classes | The total number of all patent applications by the focal firm in the firm's core patent classes by the focal firm in the given year that were eventually granted by the USPTO. | 1.506 | 7.685 | 0 | 304 |
| Patents in non-core classes | The total number of all patent applications by the focal firm in the firm's non-core patent classes in the given year that were eventually granted by the USPTO. | 0.868 | 5.922 | 0 | 335 |
| Backward self-citations | The proportion of the total number of self-citations a firm has cited in all its patent applications filed in a given year (eventually granted) to the total number of all citations (both self-citations or external) made of the firm's patent applications filed in the same year (eventually granted). | 0.014 | 0.047 | 0 | 1 |
| Backward self-citations in core classes | The proportion of the total number of self-citations a firm has made within its core patent classes for patent applications filed in a given year (which are eventually granted) to the total number of all citations (both self-citations and external) in the firm's patent applications (eventually granted) filed in the same year within its core patent (CPC) classes. | 0. 015 | 0. 051 | 0 | 1 |
| Backward self-citations in non-core classes | The proportion of the total number of self-citations a firm has made within its non-core patent classes for patent applications filed in a given year (which were eventually granted) to the total number of all citations (both self-citations and external) in the firm's patent applications (eventually granted) filed in the same year within its non-core patent classes. | 0. 005 | 0. 030 | 0 | 1 |

| | | | | | |
|---|---|---|---|---|---|
| Citation-weighted patents | Total number of forward citations of the focal firm's patents in a given year divided by the number of the firm's patent applications (eventually granted) in the given year. | 3.638 | 12.309 | 0 | 468 |
| Citation-weighted patents in core classes | Total number of forward citations of the focal firm's patents in a given year divided by the number of patent applications (eventually granted) in the firm's core patent classes in the given year. | 3.153 | 12.019 | 0 | 468 |
| Citation-weighted patents in non-core classes | Total number of forward citations of the focal firm's patents in a given year divided by the number of patent applications (eventually granted) in the firm's non-core patent classes in the given year. | 0.994 | 6.367 | 0 | 288 |
| **Explanatory variable** | | | | | |
| Post-blockage | For the treatment group (blockage equals 1), post-blockage takes the value of 1 in the observation year following the year the blockage event occurred in that sector, and 0 in the years before that; for the control group (blockage equals 0), post-blockage takes on the value of 0 throughout the sample period | 0.428 | 0.495 | 0 | 1 |
| **Control variables** | | | | | |
| Cumulative patents | The focal firm's cumulative number of patents since its foundation. | 25.797 | 168.537 | 0 | 4631 |
| Firm age | The natural logarithm of firm age. | 2.030 | 0.610 | 0 | 2.944 |
| IPO indicator | For a firm that had never been publicly listed throughout the observation period, *IPO indicator* takes the value of 0. For a firm that had been publicly listed, *IPO indicator* takes the value of 1 for the first year it was been publicly listed, and 0 in the years previous to its public listing. | 0.029 | 0.167 | 0 | 1 |
| Backward citations number | The total number of backward citations cited by a firm in all its patent applications filed in a given year (eventually granted). | 213.211 | 1318.136 | 0 | 54676 |

**Table 2. Correlations**

| Variables | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 Number of patents | 1.000 | | | | | | | | | | | | | |
| 2 Patents in core classes | 0.944 | 1.000 | | | | | | | | | | | | |
| 3 Patents in non-core classes | 0.903 | 0.711 | 1.000 | | | | | | | | | | | |
| 4 Backward self-citations | 0.116 | 0.119 | 0.093 | 1.000 | | | | | | | | | | |
| 5 Backward self-citations in core classes | 0.113 | 0.115 | 0.090 | 0.943 | 1.000 | | | | | | | | | |
| 6 Backward self-citations in non-core classes | 0.167 | 0.161 | 0.148 | 0.313 | 0.242 | 1.000 | | | | | | | | |
| 7 Citation-weighted patents | 0.073 | 0.077 | 0.054 | 0.087 | 0.083 | 0.050 | 1.000 | | | | | | | |
| 8 Citation-weighted patents in core classes | 0.068 | 0.086 | 0.034 | 0.078 | 0.073 | 0.056 | 0.883 | 1.000 | | | | | | |
| 9 Citation-weighted patents in non-core classes | 0.135 | 0.128 | 0.121 | 0.070 | 0.073 | 0.167 | 0.330 | 0.264 | 1.000 | | | | | |
| 10 Post-blockage | 0.023 | -0.004 | 0.055 | 0.029 | 0.024 | 0.033 | -0.045 | -0.070 | 0.002 | 1.000 | | | | |
| 11 Cumulative patents | 0.591 | 0.560 | 0.531 | 0.117 | 0.120 | 0.153 | 0.022 | 0.020 | 0.071 | 0.050 | 1.000 | | | |
| 12 Firm age | 0.056 | 0.053 | 0.050 | 0.118 | 0.114 | 0.066 | -0.130 | -0.121 | -0.027 | 0.138 | 0.066 | 1.000 | | |
| 13 IPO indicator | 0.165 | 0.169 | 0.131 | 0.145 | 0.144 | 0.121 | 0.003 | 0.000 | 0.033 | 0.029 | 0.132 | 0.120 | 1.000 | |
| 14 Backward citations number | 0.641 | 0.617 | 0.562 | 0.081 | 0.079 | 0.122 | 0.117 | 0.109 | 0.170 | 0.000 | 0.334 | 0.036 | 0.094 | 1.000 |

*Note*: The number of observations is 21,180. All correlation coefficients with a magnitude (absolute value) of 0.02 and above are significant at the 0.05 level.

**Table 3. Analysis of overall patented innovations**

| Model Number | 3-1 | 3-2 |
|---|---|---|
| Model | FE Poisson | |
| DV | Number of patents | Number of patents |
| Post-blockage | -0.2976$^{***}$ | -0.2016$^{***}$ |
| | (0.1053) | (0.0754) |
| Cumulative patents | | 0.0004$^{***}$ |
| | | (0.0001) |
| Firm age | | 0.5243$^{**}$ |
| | | (0.2200) |
| IPO indicator | | 0.2207$^{*}$ |
| | | (0.1260) |
| Constant | 2.7474$^{***}$ | 1.2599$^{**}$ |
| | (0.0545) | (0.5088) |
| Firm fixed effects | YES | YES |
| Year fixed effects | YES | YES |
| Observations | 19262 | 19262 |
| Log pseudolikelihood | -28690 | -28210 |

*Note*: Standard errors are clustered at the firm level and reported in parentheses. All tests are two-tailed and include constant.

$^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

**Table 4. Analysis of overall patented innovations in core areas of technological competencies**

| Model Number | 4-1 | 4-2 | 4-3 | 4-4 |
|---|---|---|---|---|
| Model | FE Poisson | | | |
| DV | Patents in core classes | Patents in core classes | Citation-weighted patents in core classes | Citation-weighted patents in core classes |
| Post-blockage | -0.3576$^{***}$ | -0.2977$^{***}$ | -0.2733$^{**}$ | -0.2630$^{**}$ |
| | (0.0956) | (0.0820) | (0.1070) | (0.1079) |
| Cumulative patents | | 0.0004$^{***}$ | | -0.0003 |
| | | (0.0001) | | (0.0003) |
| Firm age | | 0.5099$^{**}$ | | 0.2811$^{**}$ |
| | | (0.2016) | | (0.1378) |
| IPO indicator | | 0.3061$^{**}$ | | 0.1164 |
| | | (0.1334) | | (0.1113) |
| Constant | 2.2408$^{***}$ | 0.8598$^{*}$ | 2.5306$^{***}$ | 2.0496$^{***}$ |
| | (0.0426) | (0.4646) | (0.0343) | (0.2473) |
| Firm fixed effects | YES | YES | YES | YES |
| Year fixed effects | YES | YES | YES | YES |
| Observations | 18279 | 18279 | 15898 | 15898 |
| Log pseudolikelihood | -22103 | -21853 | -58327 | -58225 |

*Note*: Standard errors are clustered at the firm level and reported in parentheses. All tests are two-tailed and include constant.

$^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

**Table 5. Quantity analysis of overall patented innovations in non-core areas of technological competencies**

| Model Number | 5-1 | 5-2 | 5-3 |
|---|---|---|---|
| Model | | FE Poisson | |
| DV | Patents in non-core classes | Patents in non-core and first-entry classes | Patents in non-core and repeated classes |
| Post-blockage | -0.0448 | 0.3069$^{*}$ | -0.1177 |
| | (0.1322) | (0.1671) | (0.1539) |
| Cumulative patents | 0.0005$^{***}$ | -0.0004 | 0.0005$^{***}$ |
| | (0.0001) | (0.0003) | (0.0001) |
| Firm age | 0.5500$^{*}$ | 0.2439 | 0.6361$^{*}$ |
| | (0.3146) | (0.1984) | (0.3859) |
| IPO indicator | 0.0907 | -0.0436 | 0.0617 |
| | (0.1649) | (0.2245) | (0.1762) |
| Constant | 0.6312 | -1.5622$^{***}$ | 0.6006 |
| | (0.7318) | (0.4260) | (0.9099) |
| Firm fixed effects | YES | YES | YES |
| Year fixed effects | YES | YES | YES |
| Observations | 9772 | 7169 | 7742 |
| Log pseudolikelihood | -12582 | -4428 | -10597 |

*Note*: Standard errors are clustered at the firm level and reported in parentheses. All tests are two-tailed and include constant.

$^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

**Table 6. Quality analysis of overall patented innovations in non-core areas of technological competencies**

| Model Number | 6-1 | 6-2 | 6-3 |
|---|---|---|---|
| Model | | FE Poisson | |
| DV | Citation-weighted patents in non-core classes | Citation-weighted patents in non-core and first-entry classes | Citation-weighted patents in non-core and repeated classes |
| Post-blockage | -0.2195 | 0.3945 | 0.0401 |
| | (0.2275) | (0.3437) | (0.1987) |
| Cumulative patents | -0.0006 | -0.0021 | -0.0017$^{*}$ |
| | (0.0005) | (0.0026) | (0.0009) |
| Firm age | 0.7243$^{**}$ | 0.4974 | 0.7017$^{**}$ |
| | (0.2855) | (0.3242) | (0.3332) |
| IPO indicator | 0.1924 | 0.2976 | 0.2586 |
| | (0.1802) | (0.3651) | (0.1938) |
| Constant | 0.8716$^{*}$ | 0.9134$^{*}$ | 0.8944 |
| | (0.5287) | (0.5313) | (0.6874) |
| Firm fixed effects | YES | YES | YES |
| Year fixed effects | YES | YES | YES |
| Observations | 6039 | 5885 | 6777 |
| Log pseudolikelihood | -22449 | -18708 | -25451 |

*Note*: Standard errors are clustered at the firm level and reported in parentheses. All tests are two-tailed and include constant.

$^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

**Table 7. Analysis of proportion of backward self-citations**

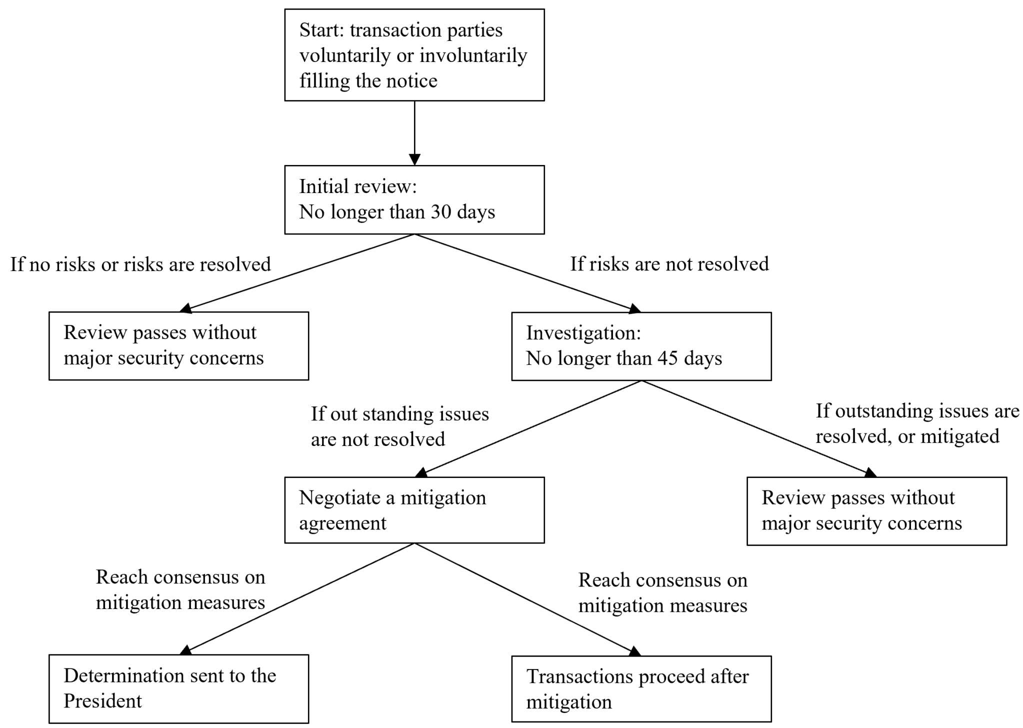
| Model Number | 7-1 | 7-2 | 7-3 | 7-4 |
|---|---|---|---|---|
| Model | | OLS | | |
| DV | Backward self-citations in core classes | Backward self-citations in core classes | Backward self-citations in non-core classes | Backward self-citations |
| Post-blockage | -0.0027* | -0.0026* | -0.0001 | -0.0017 |
| | (0.0014) | (0.0014) | (0.0010) | (0.0013) |
| Cumulative patents | | 0.0000 | 0.0000* | 0.0000 |
| | | (0.0000) | (0.0000) | (0.0000) |
| Firm age | | 0.0031* | 0.0018* | 0.0026* |
| | | (0.0016) | (0.0010) | (0.0015) |
| IPO indicator | | 0.0269*** | 0.0070** | 0.0261*** |
| | | (0.0056) | (0.0029) | (0.0049) |
| Constant | 0.0164*** | 0.0084** | 0.0006 | 0.0085** |
| | (0.0007) | (0.0036) | (0.0022) | (0.0033) |
| Firm fixed effects | YES | YES | YES | YES |
| Year fixed effects | YES | YES | YES | YES |
| Observations | 19394 | 19394 | 19394 | 19394 |
| $R^2$ | 0.2536 | 0.2596 | 0.1959 | 0.2791 |

*Note*: Standard errors are clustered at the firm level and reported in parentheses. All tests are two-tailed and include constant.

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

# Appendix

## Figure A1. CFIUS screening process




Source: Congressional Research Service

## Figure A2. Geopolitical distribution of the sample

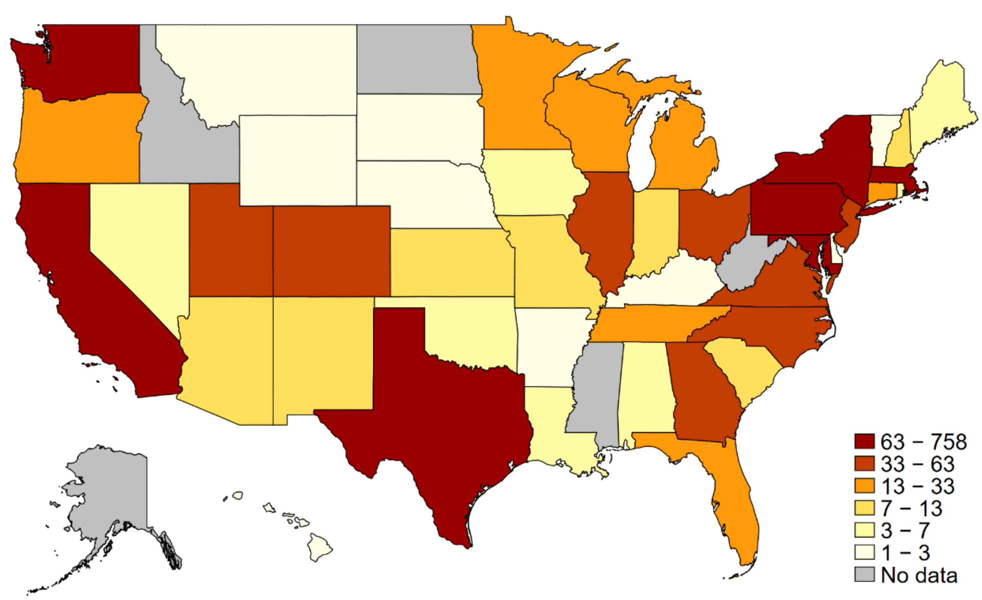


**Table A1. Acquisitions blocked by CFIUS**

| Year | Proposed Investors | Proposed Investees | Targeted NAICS | Presidential Order |
|---|---|---|---|---|
| 2008 | Huawei & Bain Capital | 3Com | 541, 334, 333, 518 | |
| 2009 | Sichuan Tengzhong Heavy Industrial Machinery Co. Ltd. | Hummer | 336, 441 | |
| 2010 | Anshan Iron and Steel Groups | Steel Development | 331 | |
| 2010 | Huawei | Sprint Nextel | 517 | |
| 2010 | Digital Sky technologies | ICQ from AOL | 541 | |
| 2011 | Huawei | 3leaf Systems | 541, 518 | |
| 2016 | Go Scale Capital | Lumileds | 336 | |
| 2016 | China Resources Microelectronics and Hua Capital Management | Fairchild Semiconductor | 334, 333 | |
| 2016 | Unisplendour Coporation | Western Digital Corporation | 334 | |
| 2016 | Fujian Grand Chip Investment Fund | Aixtron SE | 541, 333, 339 | YES |
| 2017 | Infineon | Cree's Wolfspeed Power | 221 | |
| 2017 | Beijing Canyon Bridge Capital Partners | Lattice Semiconductor | 334, 333 | YES |

**Table A2. Robustness check: Analysis of backward citations number**

| Model Number | A2-1 | A2-2 | A2-3 | A2-4 |
|---|---|---|---|---|
| Model | FE Poisson Model | | | |
| DV | Number of backward self-citations in core classes | Number of backward self-citations in core classes | Number of backward self-citations in non-core classes | Number of backward self-citations |
| Post-blockage | -0.5692$^{*}$ | -0.5102$^{**}$ | -0.4055 | -0.4457$^{**}$ |
| | (0.3316) | (0.2208) | (0.3110) | (0.2119) |
| Cumulative patents | | -0.0007$^{***}$ | -0.0001 | -0.0004$^{*}$ |
| | | (0.0002) | (0.0002) | (0.0002) |
| Firm age | | 1.2752$^{***}$ | 0.7508 | 1.0006$^{**}$ |
| | | (0.3763) | (0.6124) | (0.4182) |
| IPO indicator | | 0.3113$^{**}$ | 0.1421 | 0.1494 |
| | | (0.1228) | (0.2118) | (0.1193) |
| Backward citations number | | 0.0001$^{***}$ | 0.0001$^{***}$ | 0.0001$^{***}$ |
| | | (0.0000) | (0.0000) | (0.0000) |
| Constant | 4.6030$^{***}$ | 1.3657 | 2.1639 | 2.3725$^{**}$ |
| | (0.1507) | (0.9014) | (1.5106) | (0.9905) |
| Firm fixed effects | YES | YES | YES | YES |
| Year fixed effects | YES | YES | YES | YES |
| Observations | 11337 | 11337 | 4466 | 6600 |
| Log pseudolikelihood | -60489 | -49468 | -22135 | -45280 |

*Note*: Standard errors are clustered at the firm level and reported in parentheses. All tests are two-tailed and include constant.
$^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

**Table A3. Robustness check: Lag results for the full sample**

| Model number | A3-1 | A3-2 | A3-3 | A3-4 | A3-5 | A3-6 |
|---|---|---|---|---|---|---|
| Model | FE Poisson Model | | | | | |
| DV | Number of patents | Number of patents | Number of patents | Number of patents | Number of patents | Number of patents |
| L.Post-blockage | -0.2417*** | | | | | |
| | (0.0932) | | | | | |
| L2.Post-blockage | | -0.2322** | | | | |
| | | (0.0952) | | | | |
| L3.Post-blockage | | | -0.2301** | | | |
| | | | (0.0992) | | | |
| L4.Post-blockage | | | | -0.0842 | | |
| | | | | (0.0914) | | |
| L5.Post-blockage | | | | | -0.0865 | |
| | | | | | (0.0801) | |
| L6.Post-blockage | | | | | | -0.0466 |
| | | | | | | (0.0732) |
| Firm age | 0.0005*** | 0.0004*** | 0.0004*** | 0.0004*** | 0.0003*** | 0.0003*** |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| IPO indicator | 0.5897* | 0.6946* | 0.7260 | 0.6962 | 1.1852* | 1.0773 |
| | (0.3151) | (0.4085) | (0.5084) | (0.5739) | (0.6195) | (0.8428) |
| Cumulative patents | 0.1694 | 0.1334 | 0.1191 | 0.2726*** | 0.1911* | 0.2280* |
| | (0.1201) | (0.1132) | (0.1088) | (0.0906) | (0.1135) | (0.1193) |
| Constant | 1.1490 | 0.9489 | 0.9391 | 0.9720 | -0.1130 | 0.1378 |
| | (0.7544) | (0.9769) | (1.2395) | (1.4021) | (1.5268) | (2.1232) |
| Firm fixed effects | YES | YES | YES | YES | YES | YES |
| Year fixed effects | YES | YES | YES | YES | YES | YES |
| Observations | 16916 | 14340 | 11879 | 9501 | 7342 | 5363 |
| Log pseudolikelihood | -25154 | -21842 | -18500 | -15019 | -11740 | -8661 |

*Note*: Standard errors are clustered at the firm level and reported in parentheses. All tests are two-tailed and include constant.

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

**Table A4. Robustness check: Lag results for patents in core patent classes**

| Model number | A4-1 | A4-2 | A4-3 | A4-4 | A4-5 | A4-6 |
|---|---|---|---|---|---|---|
| Model | FE Poisson Model | | | | | |
| DV | Patents in core classes | Patents in core classes | Patents in core classes | Patents in core classes | Patents in core classes | Patents in core classes |
| L.Post-blockage | -0.3500*** | | | | | |
| | (0.0964) | | | | | |
| L2.Post-blockage | | -0.2596*** | | | | |
| | | (0.0990) | | | | |
| L3.Post-blockage | | | -0.2530** | | | |
| | | | (0.1028) | | | |
| L4.Post-blockage | | | | -0.0718 | | |
| | | | | (0.0919) | | |
| L5.Post-blockage | | | | | -0.1050 | |
| | | | | | (0.0917) | |
| L6.Post-blockage | | | | | | -0.0002 |
| | | | | | | (0.0851) |
| Firm age | 0.0004*** | 0.0004*** | 0.0004*** | 0.0003*** | 0.0003** | 0.0003** |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| IPO indicator | 0.6590** | 0.7878** | 0.9309** | 1.0854* | 1.7713*** | 1.8693** |
| | (0.3043) | (0.3953) | (0.4720) | (0.5625) | (0.6255) | (0.9215) |
| Cumulative patents | 0.2576** | 0.2285** | 0.2259** | 0.3407*** | 0.2860*** | 0.3409*** |
| | (0.1223) | (0.1139) | (0.0998) | (0.0895) | (0.1058) | (0.1263) |
| Constant | 0.5503 | 0.2475 | -0.0474 | -0.4474 | -2.0400 | -2.3652 |
| | (0.7267) | (0.9498) | (1.1497) | (1.3754) | (1.5382) | (2.3136) |
| Firm fixed effects | YES | YES | YES | YES | YES | YES |
| Year fixed effects | YES | YES | YES | YES | YES | YES |
| Observations | 15872 | 13395 | 10956 | 8668 | 6603 | 4757 |
| Log pseudolikelihood | -19331 | -16781 | -14209 | -11591 | -9106 | -6713 |

*Note*: Standard errors are clustered at the firm level and reported in parentheses. All tests are two-tailed and include constant.

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