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Patent disclosure and venture financing: The impact of the American Inventor's Protection Act on corporate venture capital investments

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Abstract

Research Summary: We investigate the effects of patent disclosure on corporate venture capital (CVC) investments in technology startups. Toward this end, we focus on the passage of the American Inventor's Protection Act (AIPA), which mandated public disclosure of patent applications. Theoretically, technology disclosure enables CVCs to better evaluate startups and thus, could increase the likelihood of investment relations. Conversely, such disclosure may already satisfy the technology-acquisition objectives of CVCs, reducing CVCs willingness to form an investment relation after disclosure. Our empirical analysis finds that patent disclosure through AIPA increased the likelihood of receiving CVC investments for startups—specifically in industries where patents have higher information significance. We provide evidence that the observed pattern is mainly driven by a reduction of information constraints regarding startups with patent applications.

Managerial Summary: Receiving corporate venture capital (CVC) funding is an important success factor for technology startups. Would disclosure of a startup's innovation increase or decrease its chance of receiving CVC funding? On the one hand, disclosure by startups would reduce uncertainty and search costs for CVC investors, which could increase the chance of CVC funding. On the other hand, such a disclosure would reveal the startups' technology to the corporations, which would in turn reduce corporate incentive to use funding as a *window to the startup's technology*. Thus, disclosure could also reduce the chance of CVC funding of startups. In this paper, we study the above issue by examining the case of the American Inventor's Protection Act (AIPA), which mandated public disclosure of patent applications. Our results suggest that innovation disclosure significantly improves the likelihood of CVC funding of startups.

KEYWORDS

American Inventor's Protection Act (AIPA), corporate venture capital (CVC), disclosure, patent, startup

1 | INTRODUCTION

After years of heated debate, in 1999, the US Congress enacted the *American Inventor's Protection Act* (hereafter AIPA) as "one of the most fundamentally significant changes to the American patent system in this century" (Campbell, 2002, p. 6). This legislative change accelerated the public disclosure of technologies featured in patent applications—to before the patent grant. Eventually, small and independent inventors—such as technology startups—became the chief opponents of AIPA, arguing that the new law was harmful for them and largely favored large corporations (see, e.g., Ergenzinger, 2006; Modigliani, 1999). Raising concerns about technology stealing and misappropriation, 26 Nobel laureates openly opposed the bill, arguing that AIPA would hurt American small inventors and technology startups (Modigliani, 1999).

The debates around AIPA are part of a more general discussion about the impacts of innovation disclosure on market outcomes (see Williams, 2017). A recent and growing body of literature has specifically focused on the disclosure effects of AIPA on markets. This literature includes works investigating the effects of disclosure on markets for technology (Hegde & Luo, 2017) and on capital markets (Beyhaghi, Khashabi, & Mohammadi, 2020; Kogan, Papanikolaou, Seru, & Stoffman, 2017; Saidi & Žaldokas, 2020). Yet, the effect of AIPA—and patent disclosure in general—on startups and their investment relationship with corporations has not yet been investigated. In this paper, we focus on the venture financing market and examine how AIPA has influenced the likelihood of corporate venture capital (CVC) investment in technology startups. The research question is relevant for several reasons. Many high-tech startups are formed around intangible assets (Graham & Mowery, 2003), and thus intellectual property (IP) disclosure reforms are potentially significant events for these entities. In addition, misappropriation concerns—which are aggravated by public disclosure—are key frictions in the venture financing market (Dushnitsky & Lenox, 2005, 2006; Katila, Rosenberger, & Eisenhardt, 2008). Given the special nature of AIPA—as a public pre-grant disclosure shock—studying its effect on the formation of the CVC–startup investment relationship would generate novel insights for market participants and policy makers.

Prior to AIPA, the United States Patent and Trademark Office (USPTO) published patent applications only *after* the patent was successfully granted. AIPA harmonized the US patent system with the rest of the world and required all patent applications to be laid open for public inspection 18 months after the initial application date—regardless of the patent's grant situation. Given that the duration of the average patent review in the USPTO was significantly longer than 18 months (Hegde & Luo, 2017), AIPA effectively disclosed key technological information about startups through their patent application, before securing patent protection (Graham & Hegde, 2015).

Several theoretical mechanisms can explain how disclosure through AIPA influences the investment relationship between CVCs and startups. On the one hand, two reinforcing mechanisms could encourage the formation of investment ties between CVCs and startups. By mandating an early public disclosure, AIPA reduces information frictions and search costs on the market (Anton & Yao, 1994, 2002; Bhattacharya & Ritter, 1983). CVC investors could therefore access the latest technologies and make more informed investment decisions regarding them. Additionally, pre-grant public disclosure without a guarantee for legal protection would encourage startups to quickly form investment ties with a CVC and to protect themselves against rivals' misappropriation through CVC's complementary assets. On the other hand, AIPA may discourage this investment relationship. Since accessing startups' technology is among the key objectives of CVCs from their investments (Benson & Ziedonis, 2009; Dushnitsky & Lenox, 2005, 2006; Katila et al., 2008), technology disclosure would already satisfy this goal and reduce their incentive to invest in startups after AIPA. The publicly disclosed technology may also be less attractive for CVCs. These mechanisms suggest opposing forces on the likelihood of investment relationships between CVCs and startups. Thus, we seek to empirically assess the resultant net effect of AIPA on the formation of CVC–startup investment ties and to analyze the boundary conditions for this effect.

To study the effect of AIPA, we focused on American startups operating in the biotech industry, where patents contain more technologically and economically significant information (Graham, Merges, Samuelson, & Sichelman, 2009; Heeley, Matusik, & Jain, 2007). To control for time trends, as a benchmark, we used American startups in the software sector, an environment in which patents contain less technologically and economically significant information. Alternatively, to account for potential industry-specific effects, we benchmarked our analysis with EU biotech startups.

The results show that after AIPA, CVC–startup investment ties in US biotech increase by 5.9% relative to US software. To ensure that the results are driven by AIPA and no other alternative explanations, we perform two additional tests. First, we show that the observed effect is driven by the subsample of startups that applied for patents (rather than startups without a patent application). This approach provides support for the role of patent application disclosure as the mechanism behind the results. Second, we show that AIPA increases the probability of CVC investment for biotech startups that applied for a patent *after* AIPA by 19.8%, relative to biotech startups that applied for a patent *prior* to AIPA. This significant difference is not observed among software startups. This approach makes a within-industry comparison and, therefore, is not exposed to industry-specific trends and shocks (e.g., the dot-com bubble). In addition, it provides empirical support for the validity of using software as a benchmark for the biotech sample in our setting.

To indicate the theoretical mechanism that generates the results, we perform additional tests using different subsamples and outcome variables. Our analyses suggest search cost and friction reduction as the main theoretical mechanism behind the positive effect of AIPA on the CVC–startup investment relationship. We show that, when there are less information constraints, the effect of AIPA is smaller—as detecting and evaluating startups in these situations was already feasible before AIPA. We do not find evidence that our results are driven by startups' rush to form investment ties with CVCs after AIPA. Indeed, our analysis indicates that after AIPA, CVC-backed startups in the biotech industry receive higher valuation and larger amounts of investment relative to software startups. These results suggest that public disclosure due to AIPA led to better matches and did not reduce the bargaining power for startups.

Our study makes several contributions to the related literature. First, by focusing on AIPA—a major IP reform—we contribute to the strand of literature on the role of IP systems in shaping the venture financing market. This literature chiefly focuses on the protection function of the IP system (Katila et al., 2008) and its consequent facilitating role in startups' voluntary disclosure (see e.g., Dushnitsky & Lenox, 2006; Dushnitsky & Shaver, 2009). We show that the mandatory public disclosure function of IP systems can directly improve the investment relationship in the startup financing market. Second, the findings highlight the role of information frictions as a limiting source of CVC investments in the venture financing market. Despite the key advantages of CVCs (Alvarez-Garrido & Dushnitsky, 2016; Chemmanur, Loutskina, & Tian, 2014), they possess a small market share in venture funding (NVCA, 2016). Our study provides evidence on how frictions render these advantages ineffective and eventually limit startups' access to valuable corporate resources. The findings support the notion that a suitable design of an IP system facilitating a transparent market environment could improve the match between startups and corporate investors. Finally, our study adds to the growing literature on the effects of AIPA on innovation and markets (see e.g., Baruffaldi & Simeth, 2020; Beyhaghi et al., 2020; Graham & Hegde, 2015; Hegde & Luo, 2017). The key debate around this IP reform was its potential adverse effects on small and independent inventors. By investigating the effect of AIPA on an important aspect of the startup–corporate relationship, we contribute to the debates around this policy reform.

2 | INSTITUTIONAL SETTING: AMERICAN INVENTOR'S PROTECTION ACT OF 1999

In this section, we discuss the institutional setting of our study, which covers the changes implemented by AIPA. We first provide a background of this law change, its goals, and the problems it was intended to solve. We then discuss the potential effects of AIPA that are relevant for our study and provide a basis for the theoretical analysis in section three.

2.1 | The AIPA bill

Patent systems are designed to have two main functions: legal *protection* and *disclosure* of invention (Gallini, 2002; Long, 2002). By securing the legal protection for inventions, patents enable the disclosure of inventions and facilitate the functioning of markets for technologies and ideas (Arora, Fosfuri, & Gambardella, 2001; Arora & Gambardella, 2010; Gans, Hsu, & Stern, 2008; Williams, 2017). AIPA—as we explain in detail below—primarily impacted the disclosure function of the US patent system. Before AIPA, there was an important feature in the US patent system that made it quite exceptional compared to the rest of the world. Unlike other major patent systems (namely that of the EU or Japan), patent application details in the US were publicly disclosed only *after* the patent was granted (Gallini, 2002). In theory, this could have taken several years (Graham & Hegde, 2015). If the application was rejected, the invention details in the patent application were never revealed. Thus, inventors—such as high-tech startups—could conceal their (unprotected) technological information in patent application documents during the application process. The old regulation gave inventors the control to choose how, when, and to whom to disclose. The passage of AIPA by the US Congress in 1999 required all patent applications filed in the US to be laid open for public inspection 18 months after the initial filing date—regardless of the patent grant situation.[1] At the time of this change, the median duration between patent application and grant was 32.5 months (Hegde & Luo, 2017). Consequently, almost all patent applications filed after AIPA's enactment date (November 29, 2000) were publicly disclosed without the guarantee of being legally protected. This act significantly amended the US patent system and implemented the “biggest changes to patent law since 1952” (Ergenzinger, 2006, p. 146).[2]

AIPA was mainly designed to make the US patent system consistent with the rest of the world, create a more transparent information environment for inventors, and reduce the probability of inadvertently working on a technology that infringed on part of another pending patent (Gallini, 2002; Graham & Mowery, 2003). In particular, the proponents of this change offered several reasons in support of AIPA. First, it constituted a move toward international harmonization of patent law. Second, AIPA made information about new technologies available earlier, cataloged, and easily searchable.[3] Thus, it could accelerate knowledge diffusion, reduce search costs, and avoid R&D

duplication. Third, early disclosure prevents the practice of "submarine patents"—that is, patent applications that are strategically kept idle for many years and finally surface to litigate an emerging technology.

2.2 | The nature of disclosure through AIPA

Before AIPA, the pre-grant public disclosure of inventions was extremely rare, which comes as no surprise; inventors, especially small and independent ones, have strong misappropriation concerns that hold them back from public disclosure of their inventions before securing legal protection. Besides this, public disclosure of a technology—beyond the "grace period"—makes it count as a "prior art" and thereby ineligible to be patented in the US (Franzoni & Scellato, 2010).[4] Given the above, pre-grant public disclosure almost never happened before AIPA. The information environment regarding new inventions was therefore significantly influenced by the public disclosure of applications required by AIPA (Hegde & Luo, 2017).

The (pre-grant) disclosure through AIPA has key distinctions compared to other disclosure channels—for example, voluntary disclosure in media or through bilateral negotiations. To begin with, information disclosure through AIPA has a public nature. Thus, the disclosed information became freely accessible to interested parties right after AIPA's enactment. In addition, as Hegde and Luo (2017) point out, information disclosed in the patent application documents is substantially more credible than other disclosures for two reasons: First, since the technology holders may risk delay or denial of their patent applications by making imprecise claims. Second, verifying the new technology in the patent application allows the technology holder to sue potential infringers and demand remedies for the period between the application disclosure and the patent grant. Therefore, inventors have the incentive to provide their technological details very precisely in the patent application documents.

While being largely credible, the pre-grant disclosure through AIPA is not comparable to post-grant disclosure (i. e., patent publication). The information disclosed in the patent applications is still *not legally protected*. There is, of course, a reasonable probability that these inventions are eventually patented. Yet, there is also an element of uncertainty involved. Risk of rejection applies to all patent applications. Even if granted, the scope of claims in patent applications often get revised during the review process. This uncertainty in the extent of legal protection makes inventors concerned about disclosing their technology, mostly due to the risk of misappropriation. We cover this issue in the next subsection.

2.3 | Concerns and criticisms

While the proponents of AIPA picture it as a legal act that improves information transparency and the functioning of the IP system, significant concerns around AIPA bill have been raised, leading to heated debates during its passage period. The debates in Congress and in the media were mostly concerned with the prospect of technology stealing, especially for entrepreneurs and small inventors incapable of protecting their inventions. Below we give an overview of these concerns.

Unlike post-grant patent disclosure—for which the government guarantees legal protection in return to disclosing the invention—after AIPA, inventors face the risk of disclosing their invention without receiving protection for it. Opponents have therefore argued that small and independent inventors—especially high-technology startups—would suffer the most from this issue. They often lack the financial, legal, and complementary assets needed to protect their disclosed technology against misappropriation (Lanjouw & Schankerman, 2004). In addition, as Campbell (2002) highlightsm, "These small entities do not have the resources to take advantage of the ability to search a larger pool of prior art. More prior art can create opportunities if you have the resources to take advantage of the opportunity. Small entities do not have these resources. They use the patent system defensively to protect their work" (p. 7). On the contrary, large companies benefit from pre-grant disclosure in a number of ways. These companies typically rely on a combination of approaches to protect their technology, so they have less misappropriation concerns because of public disclosure. Instead, they use this disclosed information to access new technologies and strategically "invent around" them. Large corporations could also use the pre-grant disclosure to reconsider their duplicative research and redirect their resources to more promising projects. The disclosure provision also helps them to better identify infringing technologies and decrease their search costs. Therefore, favoring large corporations, AIPA puts the inventions of tech startups at risk of misappropriation.

The above issues shaped the main concern regarding AIPA during its passage period. For instance, the 18-month disclosure provision was strongly opposed by some members of Congress and was considered "a major catastrophe" for independent inventors, and "a sweetheart deal" for big business and large international companies (Ergenzinger, 2006, p. 154). Rep. Rohrabacher argued that early public disclosure would allow large multinational corporations to misappropriate technology from independent inventors, and he sarcastically labeled it the "Steal American Technology Bill" (Ergenzinger, 2006, p. 154). In an open letter to the US Senate, 26 Nobel laureates opposed the bill due to its early public disclosure requirement. The letter warned that the bill "could result in lasting harm to the United States and the world" and that it would hurt "small inventors" (Modigliani, 1999, p. 1).

As depicted above, the key debated advantages (i.e., transparency and reduction of information friction) and disadvantages (i.e., technology misappropriation) of AIPA are directly relevant for the venture financing market and in particular for the corporate–startup relationship. This motivates an analysis of the effect of AIPA on this particular context, as discussed in the next section.

3 | STARTUP FINANCING MARKET AND AIPA

To study the impact of AIPA on the startup–CVC investment relationship, we analyze the theoretical forces stemming out of this change in the startup financing market. In this section, we first introduce the startup financing market players and then discuss how AIPA may influence the CVC–startup relationship from the supply-side and demand-side perspectives.

3.1 | The startup financing market

The market for startup financing consists of startups (the demand side) and investors (the supply side). Technology startups— that is, startups based on a new technology or invention—are very active in this market, competing to acquire essential resources from investors. Many startups acquire IP rights, and this pattern is stronger in technology-intensive industries where startups are typically built around intangible capitals. Graham et al. (2009) report that 82% of high-technology VC-backed startups hold at least one patent.

The supply side on this market is typically comprised venture capitalists, who make risky early-stage equity investments in startups (Gompers & Lerner, 2000, 2004). There is a stark distinction between venture capital investors that is related to their connection to incumbent corporations. While independent venture capitals (IVCs) are private equity investors with no direct connection to corporations, corporate venture capitals (CVCs) belong or are closely linked to incumbent corporations (Colombo & Shafi, 2016; Dushnitsky & Shaver, 2009; Gompers & Lerner, 2000). Our focus in this study is on the relation of startups with the latter investors—which AIPA potentially impacts.

CVCs not only provide capital but are also providers of complementary assets, such as manufacturing facilities, distribution channels, and industry endorsements (see, e.g., Dushnitsky, 2012; Gompers & Lerner, 2000; Katila et al., 2008; Maula, 2007). However, unlike in the case of IVCs, CVCs consider startup financing not only as an investment for financial return but also largely as a *window to new technology* (e.g., Benson & Ziedonis, 2009; Dushnitsky & Lenox, 2005, 2006). Surveys from CVC managers have revealed that this strategic objective ranks as the primary goal of CVCs for their investment, whereas other objectives, such as financial return, are ranked lower (Alter & Buchsbaum, 2000; Siegel, Siegel, & MacMillan, 1988; Yost & Devlin, 1993). Consistent with the CVC objectives described above, academic research has also documented evidence that startups are concerned with technology misappropriation by CVCs, which complicates the formation of investment relations between them (see e.g., Dushnitsky & Shaver, 2009; Katila et al., 2008). These studies highlight that startups are concerned that CVCs may "... exploit the information, imitate the invention, and leave the entrepreneur empty-handed" (Dushnitsky & Shaver, 2009, p. 1046). This concern is more serious in weaker IP regimes (Dushnitsky & Shaver, 2009). As a result, CVC investors face rampant informational constraints about startups' technology compared to other investors in the venture financing market (Colombo & Shafi, 2016; Dushnitsky & Shaver, 2009).

3.2 | AIPA and the supply side of venture financing

The changes implemented after AIPA may influence the willingness of CVCs to invest in startups through two counteracting mechanisms: reduction of search cost and satisfying their strategic objectives—that is, technology acquisition. Regarding the former, the literature on entrepreneurial finance has highlighted the role of search costs as a barrier to forming investment relations between startups and venture capitalists (Eisenhardt & Schoonhoven, 1996; Hsu, 2006). The search costs correspond to efforts to find potentially suitable startups and to investigating the quality of these ventures. CVCs largely aim to diversify their portfolios on a wide range of activities that span across industrial segments. As mentioned above, their key objective is to use these investments as a window to new technologies and to observe the technological space. Therefore, when detecting relevant and remarkable technologies, CVCs have relatively unconstrained capital supply to form ties with these startups. Quoting from Chemmanur et al. (2014), CVCs "... are not contractually limited in their ability to draw capital from a parent company as needed. However, IVCs' fund-draws are limited by the amount of capital initially committed by their limited partners" (p. 2441).

Yet, unlike specialist IVCs, CVCs face information disadvantages in detecting suitable startups. First, CVCs have limited access to entrepreneurial networks. Without proper information intermediaries, CVCs may simply not be aware of potentially suitable startups from diverse fields in which to invest (Gans, Hsu, & Stern, 2002). It is also difficult for CVCs to verify the quality of these targets, as startups are reluctant to reveal their technology to CVCs. This problem is not as significant for IVCs. Of course, CVCs can wait for uncertainty to be resolved, relegating their investment decisions to more mature stages. But this already implies accepting the risk of losing attractive investment options to rivals, or facing lower bargaining power in the negotiation with mature high-potential startups, which is considered a lost opportunity (Cochrane, 2005; Nanda & Rhodes-Kropf, 2013).

The changes implemented by AIPA directly facilitate the above process. First, by creating a transparent information environment, AIPA has significantly reduced frictions and search costs in the market of venture financing. Providing a cataloged and searchable information platform regarding new technologies, AIPA enables CVCs to detect and access startups from diverse industrial fields. AIPA also significantly reduces the baseline information asymmetry—between investor and startup—in favor of CVCs. When the technological details of patents are published during the application, CVCs could access this information and use it to detect higher-quality startups. As a result, the adverse-selection concern, which typically holds back CVCs, would drop significantly post-AIPA. In addition, post-AIPA, CVCs could not only better evaluate a tech startup but also compare its technology to other close substitutes, assess their (dis)advantages, and make more-informed decisions. Given that CVCs are not strictly resource-constrained, detecting more suitable investment options with lower risks would imply allocating more resources to venture financing from the corporate parent, and eventually leading to greater investment likelihood.

Second, AIPA improves the timing of technology access for CVCs. The value of technology is quite sensitive to timing; outdated technologies have significantly lower value in the market. Survey studies report issues such as being "out of date," "behind the state of art technology," and "released too late for cutting edge research" as important obstacles to the effective use of patents (Ouellette, 2012, p. 558). By accelerating the timing of innovation disclosure, AIPA alleviates the above concerns, especially for CVCs, which typically accessed startups' technology quite later than other investors—that is, after the technology is being patent-protected. Improving timing provides a larger pool of technologically attractive startups with higher investment returns and increases the likelihood of CVC investments.

Finally, as a public disclosure, AIPA reduces the search costs for all the potential investors in the startup financing market. Therefore, CVCs face greater competition among themselves in forming investment ties with high-potential startups. This would drive CVCs to reach out faster to startups to stay ahead of their corporate rivals, which could drive tie formation in earlier startup stages. The friction and search cost reduction mechanism, overall, predicts a higher likelihood of an investment relationship between CVCs and startups. Moreover, this perspective would imply higher startup valuation and bargaining power, due to increased supply-side competition effects.

Unlike the market friction mechanism, the effect of AIPA in satisfying the strategic objectives of CVCs points to the opposite direction. The entrepreneurial finance literature stresses the strategic objectives that CVCs have from their investments (e.g., Benson & Ziedonis, 2009; Dushnitsky & Lenox, 2005; Dushnitsky & Shaver, 2009; Hellmann, 2002; Katila et al., 2008). As this stream of work reports, CVC investment decisions are chiefly targeted at accessing startups' technology (e.g., Gompers & Lerner, 2000; Siegel et al., 1988; Yost & Devlin, 1993). Post-AIPA, a CVC has already gained a big chunk of information about the startup's technology. Thus, the technology acquisition objective of the CVC is largely satisfied. Through this perspective, a technology startup post-AIPA may have less value for CVCs. In addition, a publicly disclosed technology may generate smaller competitive advantage for its owners. Thus, CVCs may have less incentive to invest in startups in the post-AIPA period. Through this mechanism, one would expect AIPA to discourage the supply side and eventually decrease the likelihood of a CVC–startup investment relationship, which leads in the opposite direction to the first mechanism. Our framework to analyze the supply side closely connects to Arrow's (1962) disclosure paradox; a technology buyer would require detailed information to evaluate a technology. However, providing that information by the seller would in fact imply transferring the technology to the buyer without receiving any share of the value. As Bloom, Van Reenen, and Williams (2019) describe, "A pitch of 'trust me, I have a great idea, so please fund me' is rarely effective, whereas a pitch of 'let me describe my not-yet-patented idea in detail' opens up the possibility of potential investors stealing an idea from the entrepreneur" (p. 168).

3.3 | AIPA and the demand side of venture financing (startup)

The above perspective analyzes the effect of AIPA on the likelihood of investment formation from the supply side. To check for the effect from the demand side, we focus on the startups' perspective. As mentioned before, in a frictionless market, technology startups have a strong preference to form investment relationships with CVCs. This is because CVCs would help startups to gain resources beyond financial capital—for example, manufacturing facilities, managerial insights, expert human resources, industry endorsements, and marketing and distribution channels (Alvarez-Garrido & Dushnitsky, 2016; Chemmanur et al., 2014).[5] IVCs clearly lack most of these resources. However, the strategic objectives of CVCs create a tradeoff for startups between enjoying CVC resources (and undertaking the misappropriation risk) or keeping their technology safe (and waiving this investor choice). After AIPA, this tradeoff became less relevant; startups post-AIPA have less ability to hide key technological information from CVCs. Therefore, CVCs already access a considerable amount of startups' technological information AIPA mandated disclosure. Consequently, refraining from collaboration with CVCs would no longer protect a startup's technology as it would have in the pre-AIPA period. Since AIPA makes startups' information public, noninvesting corporates can also access this information. IP protection in this stage is not guaranteed to protect the disclosed technology. Therefore, startups are better off collaborating with a CVC in order to protect their technology via the complementary resources of the corporate. Since CVCs possess higher levels of complementary assets, forming a tie with them can lead to faster commercialization and first-mover advantage, which is an effective strategy in situations where other protection mechanisms are absent (see e.g., Arora et al., 2001; Arora & Ceccagnoli, 2006).[6] Delays in forming investment relationships with a CVC may result in technology misappropriation by corporate competitors and the loss of a startup's competitive advantage. This perspective implies an increase in the demand from the startups' side, which leads to a higher likelihood of a CVC–startup investment relationship. This higher demand and rush to form investment relations with CVCs may come at the cost of smaller bargaining power for startups after AIPA.

3.4 | Heterogeneity in the effect of AIPA

One should note that the information significance of patent documents is not uniform across industries (Cohen, Nelson, & Walsh, 2000; Graham et al., 2009). As Heeley et al. (2007) discuss, in some industries, the link between the patent and the product in the market is more transparent. In such industries, for example, biotech, patents are important sources of technological information. They may contain information on why the previous inventions were inefficient and can clearly indicate the superior elements of the current invention. Given this major role, competitors, investors, and stakeholders will carefully read patent documents to make sure they are aware of recent developments (Knight, 2012). For this very reason, many prior studies on the relationship between patents and startup financing focus on the *biotech* sector (see e.g., Alvarez-Garrido & Dushnitsky, 2016; Baum & Silverman, 2004; Haeussler, Harhoff, & Mueller, 2014; Stuart, Hoang, & Hybels, 1999).

Unlike biotech, there is another category of industries where patents are informationally less significant (Heeley et al., 2007). In software industry for example, patent documents do not reveal much relevant information about the product (Cohen & Lemley, 2001). For instance, the source code of software is not legally required to be included in the patent document. Therefore, reverse engineering a software, even with access to its patent document, is usually impractical.[7] Accordingly, software patent documents are considered less—technologically and informationally—relevant than biotech patents. Evidence from survey studies is consistent with this distinction. A recent survey of startup founders showed that 59% of biotech startups that did not seek patent protection mentioned that they "did not want to disclose" as a main reason, while this response for software was just 25% (Graham et al., 2009). A large survey of European Patent Office (EPO) inventors also reports that in biotech, patents are a key source of information for R&D personnel, while they are less relevant in software (PatVal EU-II survey).

In our study, we take advantage of this heterogeneity in several ways to build our empirical strategy. In line with the literature, we also focus on startups in the biotech industry to investigate the information disclosure effect of AIPA on CVC investments. To capture the potential contaminating effects of time trends and country/industry-specific shocks, we benchmark our analyses with several samples that (a) AIPA is expected to have a smaller impact on, and that (b) are exposed to similar time trends and country or industry-specific shocks. This approach enables us to measure the actual effect of AIPA with less contamination. As one of the main benchmarks, we focus on American software startups. This sample shares the same *institutional setting* and *country-level trends* with American biotech startups. To address concerns regarding *industry-specific shocks*, we use an alternative benchmark—that is, EU biotech—as an additional analysis. Finally, we take advantage of this heterogeneity to run within-industry analyses comparing startups that have patented before vs. after AIPA, once in the biotech and once in the software sample, to investigate their distinctions.[8] The next section describes our empirical strategy in further detail.

4 | METHODS

4.1 | Data

To study the effect of AIPA on the likelihood of a CVC–startup investment relationship, we build a sample of VC-backed startups in the US using the SDC Platinum database. SDC Platinum is the standard database that the CVC literature uses in studies that focus on startup financing (see e.g., Dushnitsky & Shaver, 2009; Gompers & Lerner, 2004; Katila et al., 2008). To build the sample, we consider all venture capital rounds of investment in the US from 1995 to 2006. The choice of this time window places AIPA's enactment year (i.e., 2000) at the mid-point of the study period. In line with previous studies (e.g., Dushnitsky & Lenox, 2005; Katila et al., 2008), we exclude investments from other financial institutions—such as banks, government-affiliated institutes, and insurance companies—and limit our study to investments deals with at least one IVC or CVC as investors.[9] We focus on biotech and software startups as two technology-intensive industries. This selection is in line with Mann and Sager (2007). The sample includes 13,703 rounds of investments in 4,957 startups. As the second step, we manually match startups to unambiguous patent assignees using the PatentsView[10] and Fung Institute databases.[11] In the matching process, we identify 1,223 startups that applied for at least one patent. These startups receive 3,768 rounds of investments.

In addition, we build a *restricted sample* for our analyses. For this sample, we focus on patenting activities within the two-year time window before/after AIPA.[12] We include startups founded prior to AIPA that have at least one patent in this sample. We use this sample to compare the likelihood of CVC investments among startups that patented before vs. after AIPA.

4.2 | Dependent variables

The focus of this paper is on examining the likelihood of an investment relationship between a CVC and a startup. To capture this likelihood in our analyses, we build the main dependent variable as a dummy indicating if at least one CVC has invested in the focal round of investment in the startup (*Deal CVC*). *Deal CVC* takes the value of *one* if at least one of the investors in the rounds of investments is a CVC; otherwise, it equals *zero*. This approach is similar to the variable definition in Katila et al. (2008) and Chemmanur et al. (2014).

4.3 | Independent variables

The first independent variable for our study is the time dummy (*Post-AIPA*), taking the value of *one* if the investment happened after the US enacted AIPA (after 2000) and *zero* if it happened before the enactment. Since AIPA's enactment date was November 29, 2000, we also exclude the years 2000 and 2001 as one of the robustness checks. In the analyses on the restricted sample, we adjust the definition of *Post-AIPA* and use the exact enactment date of AIPA (November 29, 2000).

To study the effects of AIPA on CVC investment, we focus on the US biotech industry as our main study sample (*Biotech* = 1) and compare it to several benchmark groups. The startups in the US software industry serve as one of our benchmarks (*Biotech* = 0). As additional tests in the Appendix, we use European startups in the biotech industry as an alternative benchmark (*US Biotech* = 0). While the first benchmark has the advantage of being in the same institutional setting (i.e., the same country and patent system), the second has the advantage of being in the same industry (i.e., biotech). We use the SDC Platinum industry classifications to build these groups.

Post Patent is another dummy variable that we use in our other specifications for within-industry benchmarking. This variable takes the value of *one* when the startup has at least one patent application up to two years *after* AIPA. A *Post Patent* equal to *zero* indicates that the startup has at least one patent application in the two years *prior* to AIPA (but no patents in the two years after AIPA).

4.4 | Control variables

In our model, we control for a wide array of variables that the literature reports to affect the likelihood of CVC investments. Investors commit capital in different rounds of investments instead of making an upfront investment of all the required capital. In each round, the information asymmetry diminishes, since investors are able to observe entrepreneurial effort and the progress of the project. To account for this, we control for the round in which the investment takes place. Since the round number is not normally distributed—following Katila et al. (2008)—we use the natural logarithm of the round number (*Round Number*). We also control for the supply of CVC venture capital in the focal year as the annual share of the total amount of CVC investments, out of the total VC investments (*Share CVC deal Flow*). To take into account competition with IVCs and entrepreneurial activities in the market, we control the number of active IVCs relative to the number of startups in the industry and per year (*IVC per Venture*). This control variable can also capture the trends in the VC market. We also control for the number of investors in each round of investment (*Syndication size*). Syndication size can ensure that the observed effect is not due to a larger number of investors in each deal. For the US sample, we control for the geographical location of the startups by inserting two dummy variables for *California* and *Massachusetts*. We control for stock market conditions using the *NASDAQ* returns in the focal year. The startup's stage of development also affects the level of information available about the startup's progress and potential. We control for the startup's stage of development with five dummies indicating whether the startup is in the "startup," "early stage," "late stage," "expansion," or "other" (the baseline category) stage. This control is built using the classification reported by SDC Platinum. Finally, we include the year fixed effect in all models. Appendix S1 reports the definitions of all the variables.

5 | EMPIRICAL SPECIFICATION

We start by estimating the specification below via a Logit model to investigate the effect of AIPA on the likelihood of CVC investments.[13] In this specification, index (*i*) refers to the startup, (*j*) represents the round of investment, and (*t*) represents time.

$$\text{Deal CVC}_{ijt} = \beta_1 + \beta_2\,\text{Post-AIPA}_t + \beta_3\,\text{Biotech}_i + \beta_4\,\text{Biotech}_i \times \text{Post-AIPA}_t + \beta_5\,\text{Z}_{\text{ijt}} + \alpha_i + Y_t + \varepsilon_{ijt}. \tag{1}$$

The coefficient of interest in Equation (1) is β_4, which varies at the (*it*) level. Z_{ijt} is a vector of control variables discussed in the previous section. We also include the startup fixed effect (α_i) in some of the models. This is only possible for the sample of startups that received at least one round of investment before and at least one round of investment after AIPA (*fixed effect sample*). Y_t denotes the year fixed effects. Standard errors are clustered at the startup level. Given that we control for the year fixed effects, we cannot estimate β_2. To address the concern about interpreting interaction terms in nonlinear models (Ai & Norton, 2003), we also report a corresponding linear probability models in Appendix S2.

To ensure that the results in Equation (1) are driven by AIPA and not alternative explanations, we use a second specification as Equation (2). We perform this analysis separately on the biotech and software startups. This also allows us to validate the choice of software startups as the benchmark sample.

$$\text{Deal CVC}_{ijt} = \theta_1 + \theta_2\,\text{Post-AIPA}_t + \theta_3\,\text{Post Patent}_i + \theta_4\,\text{Post Patent}_i \times \text{Post-AIPA}_t + \theta_5\,Z_{ijt} + \alpha_i + Y_t + \varepsilon_{ijt}. \tag{2}$$

Equation (2) is estimated by a Logit model on the *restricted sample*. Post-AIPA$_t$ is a dummy variable indicating whether the investment happened after the enactment of AIPA (we use the exact date of AIPA's enactment, November 29, 2000). As discussed in the variable section, Post Patent$_i$ indicates whether the startup has at least one patent application (up to 2 years) before or after AIPA. The coefficient of interest is θ_4, which varies at the (*it*) level. Similar to Equation (1), Z_{ijt} is a vector of control variables, and Y_t denotes the year fixed effects. Standard errors are clustered at the startup level.[14]

6 | RESULTS

In this section, we first focus on the effect of AIPA on CVC investment. After establishing the effect, we explore the possible mechanisms discussed in the theory section and report several additional tests.

6.1 | AIPA and likelihood of CVC investment

US Biotech vs. *US Software startups*. In this section, we investigate whether AIPA had an effect on the likelihood of CVC investment in the biotech startups, compared to our benchmark group (software). We start with a univariate analysis. Table 1 reports that after AIPA, the likelihood of CVC investment increases by around 10.5% for US biotech startups, relative to the US software startups. This effect is statistically significant ($p < .01$).

Next, we use multivariate analysis, which allows us to control for several additional variables. Table 2 reports the estimation results for Equation (1). In Column 1, we compare the effect of AIPA on the US biotech vs. US software startups. The coefficient of interaction between *Post-AIPA* and *Biotech* is positive and significant (Model 1: beta = 0.439, p = .007). This is consistent with univariate analysis. Given the complexity in interpreting the magnitude and the statistical significance of the interaction terms in nonlinear models, we graphically plot the marginal effects corresponding to Logit regression in Figure 1. In addition, we report the coefficients of a linear probability model (Appendix S2, Column 1). The interaction coefficient (Appendix S2, Model 1: beta = 0.060, p = .004) implies that AIPA increases the probability of CVC investment for biotech startups by 6% (31.5% of the mean of sample) relative to software startups.

Our quasi-experimental methodology assumes that startups (within US biotech and software in our sample) are not systematically different in the pre and post AIPA periods. To ensure that our results are not affected by this assumption, we perform two additional analyses. In Column 2 of Table 2, we repeat our analysis on a subsample of startups that received at least one round of investment before AIPA and one round after AIPA (*Fixed effect sample*). This sample contains the same startups before and after AIPA. This setting is very similar to a difference-in-differences analysis and allows us to include startup fixed effect. Moreover, in Column 3, we take an alternative approach to address this concern, and we match each post-AIPA observation (within biotech and within software) to one observation pre-AIPA using the propensity score matching. We use all control variables in the matching process. The coefficient of interaction between the *Post-AIPA* and *Biotech* is positive and statistically significant in both models (Model 2: beta = 0.732, p = .007; Model 3: beta = 0.537, p = .005). The coefficient in the *fixed effect sample* (Appendix S2-Model 2: beta = 0.114, p = .046) implies that after AIPA, the probability of CVC investment increases for biotech startups by 11.4% relative to software startups. These results provide further empirical evidence that after AIPA, the CVC investment in biotech startups increases.

The effect of AIPA in our theoretical arguments is related to patent application documents. Hence, using all startups (of which some might not have patents) can create noise in the estimated effect of AIPA. To address this issue, we estimate Equation (1) separately for a subsample of startups, which we could match with patent assignees in the USPTO (Column 4), and a subsample of startups, which we could not match with patent assignees in the USPTO (Column 5). If the observed effect in Column 1 is truly due to AIPA, we expect to observe a stronger effect

TABLE 1 Univariate test of differences in likelihood (Deal CVC) of CVC investment pre- and post-AIPA

Dep var.: Deal CVC				
	N	Pre-AIPA	Post-AIPA	Differences
US Biotech	2,939	0.183	0.263	0.079
US Software	10,764	0.188	0.162	−0.026
Differences				0.105***

TABLE 2 The effect of AIPA on likelihood of receiving investment from CVC using logit model

Sample Main group Benchmark	US Biotech US Software (1) Full	 (2) Fixed effect	 (3) PSM	US Biotech US Software (4) With patent	 (5) Without patent	Patent post-AIPA Patent pre-AIPA (6) Restricted (biotech)	 (7) Restricted (software)
Biotech	−0.073		−0.167	−0.358*	−0.061		
	(0.143)		(0.168)	(0.185)	(0.230)		
Post-AIPA × Biotech	0.439***	0.732***	0.537***	0.640***	0.380		
	(0.162)	(0.271)	(0.192)	(0.222)	(0.255)		
Post-AIPA × post patent						1.554*	0.113
						(0.897)	(0.828)
Post patent						−0.157	0.071
						(0.678)	(0.424)
Round number (ln)	−0.004	0.390***	−0.011	0.108	−0.053	0.485**	0.299
	(0.055)	(0.143)	(0.060)	(0.092)	(0.069)	(0.238)	(0.219)
Share CVC deal flow	2.162***	0.604	5.486***	0.940	6.176***	−246.092*	202.793*
	(0.377)	(2.250)	(1.545)	(1.685)	(1.706)	(134.700)	(109.265)
IVC per venture	−3.127***	−2.294	−3.494	−13.899***	2.213	33.022	−36.123*
	(0.933)	(4.627)	(3.422)	(4.198)	(3.615)	(22.937)	(19.019)
Syndication size	0.326***	0.461***	0.342***	0.302***	0.336***	0.189***	0.445***
	(0.014)	(0.022)	(0.018)	(0.024)	(0.018)	(0.050)	(0.052)
California	0.137*		0.089	0.054	0.158*	0.032	0.451
	(0.072)		(0.080)	(0.130)	(0.087)	(0.317)	(0.295)
Massachusetts	−0.101		−0.039	−0.011	−0.177	−0.369	0.605
	(0.104)		(0.114)	(0.178)	(0.127)	(0.441)	(0.426)
Nasdaq	−0.159**	3.030	−0.863	−3.829**	1.789	−3.180	2.919
	(0.069)	(2.076)	(1.430)	(1.617)	(1.567)	(2.381)	(2.018)
N	13,703	4,922	9,963	3,768	9,937	471	701
No. startups	4,957	1,096	4,343	1,223	3,735	175	241
Chi-square (*p* value)	.000	.000	.000	.000	.000	.000	.000

Notes: The corresponding linear probability model is reported in Appendix S2. Model 1 includes biotech and software VC backed startups in US. Model 2 includes startups that received at least one round of investment before AIPA and at least one round of investment after AIPA. The model includes startup fixed effect. Model 3 report the results after the propensity score matching, PSM (within biotech and within software) between observations pre and post AIPA. Model 4 includes biotech and software VC backed startups in US that that applied to at least one patent. Model 5 includes biotech and software VC backed startups in US that we could not find any patent application for them. Model 6 includes biotech VC backed startups (1998–2003) in US which are founded prior AIPA and have at least a patent up to 2 years prior AIPA (post patent = 0) or a patent up to 2 years after AIPA (post patent = 1). Model 7 includes software VC backed startups (1998–2003) in US which are founded prior AIPA and have at least a patent up to 2 years prior AIPA (post patent = 0) or a patent up to 2 years after AIPA (post patent = 1). In all models (except model 2), clustered robust standard error is reported in parentheses. In model 2, robust standard error is reported in parentheses since "xtlogit" command in Stata does not support cluster option; *, **, or *** indicate statistical significance at the 10, 5, and 1% level, respectively. All models include year and stage of development fixed effect.

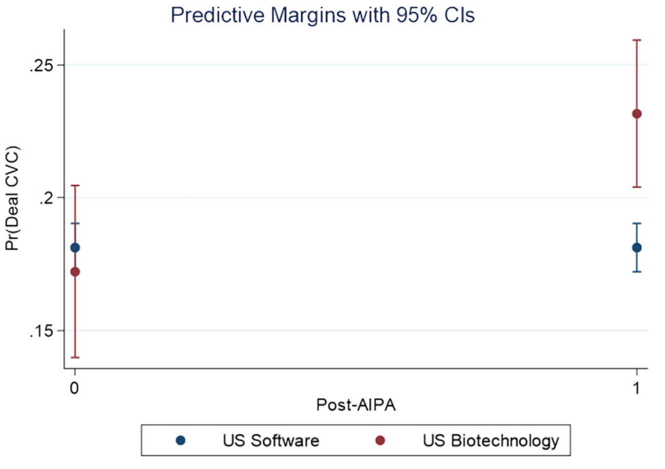

FIGURE 1 Marginal effect for US biotech and US software startups after logit model in Table 2, Column 1 [Color figure can be viewed at wileyonlinelibrary.com]

for startups with patents relative to startups without patents. The results provide supporting evidence, as the estimated coefficient for startups with patents is quite larger (Model 4: beta = 0.640, p = .004) relative to startups without patents (Model 5: beta = 0.380, p = .135). The linear probability estimates (Appendix S2, Model 4: beta = 0.097, p = .003) imply that after AIPA, the probability of CVC investment increases for biotech startups with patents by 9.7% relative to software startups with patents. For startups without patents, the effect is smaller and is not statistically significant (Appendix S2, Model 5: beta = 0.045, p = .130).[15] The lack of statistical significance cannot be due to small sample size, since the number of observations in the sample without patents (N = 9,937) is significantly larger than the number of observations in the sample of startups with patents (N = 3,768).

As the final step, we dig deeper into the patent data and, in addition to matching startups with patents (results in Column 4), we use the timing of patent applications. Columns 6 and 7 report the estimation results for Equation (2). Column 6 (N = 471) reports the results for biotech startups, while Column 7 (N = 701) reports the results for the software startups. The results show that biotech startups that applied for a patent right after AIPA (Post Patent = 1) are significantly more likely to receive CVC investment relative to biotech startup that applied for a patent prior to AIPA (Model 6: beta = 1.554, p = .083). The relatively lower significance level for this estimate could be due to the small number of observations. The corresponding coefficient in the linear probability model (Appendix S2, Model 6: beta = 0.198, p = .084) implies that AIPA increases the probability of CVC investment for biotech startups that applied for a patent right after AIPA (Post Patent = 1) by 19.8% relative to startups that applied for a patent prior to AIPA. However, as Column 7 in Table 2 shows, there is not such a difference among software startups (Model 7: beta = 0.113, p = .891). These results provide further evidence that the effect is caused by AIPA and is more salient for biotech startups relative to software startups.

Each of the specifications presented above have certain advantages and disadvantages. However, as a whole, they provide empirical support that after AIPA, CVC investment in US-based biotech startups increased relative to US-based software startups, and that the effect is driven by AIPA—not by alternative explanations (e.g., industry-specific shocks, such as the dot.com bubble).

6.2 | Mechanism test

Overall, the results of our main analyses reveal a positive effect of AIPA on the CVC–startup investment relationship. In this section, we seek to understand the theoretical mechanisms behind this positive effect, within our data constraints.

The arguments in the theory section inform two mechanisms by which AIPA could positively impact CVC investments: (i) search cost and friction reduction (impacting the supply side), and (ii) higher advantage for startups to form ties with a CVC—for example, protection via complementary assets (impacting the demand side). These mechanisms are not necessarily substitutes and can drive the results together. Here, we use three sets of analyses to better understand the mechanisms behind the results: (a) heterogeneity in information constraints and search costs faced by CVCs, (b) hazard of investment, and (c) startup valuation.

6.2.1 | Heterogeneity in information constraints

We run several analyses dedicated to testing the search cost reduction effect of AIPA. For this purpose, we consider cases with different levels of information constraints and compare the effect of AIPA across them. If search cost reduction is one of the mechanisms driving our results, we expect to find smaller effects when the information constraints are lower, as detecting and evaluating startups in these cases was already feasible before AIPA. We consider three cases with lower information constraints: (i) where startups are in the later stages of development; (ii) where startups enjoyed an affiliation with a prominent IVC; and (iii) where they already received investment from a CVC in prior rounds of investment. In all three cases, we argue that reduction of search cost due to public disclosure (AIPA) should have a weaker impact on CVC investments compared to cases with strong information constraints.

For the first case, we focus on startups' stage of development. Typically, a startup's stage of development indicates their commercial potential and maturity (e.g., Ahuja, 2000; Gompers, 1995; Rothaermel & Deeds, 2004). On the contrary, there is an intrinsic uncertainty in the earlier stages of startup development. Thus, startups that are in the earlier stages of development pose greater information asymmetries and risk to CVC investors (Gompers, 1995; Sahlman, 1990). Moreover, startups in the earlier stages impose stronger information constraints on CVCs, as they are more concerned about misappropriation due to lack of financial, social, and complementary resources to defend their technological assets (Katila et al., 2008). We therefore expect search costs to be more pronounced when startups are in the earlier development stages (i.e., the "startup stage"). Consistent with the search cost reduction mechanism, Table 3 shows that the effect of AIPA is largest at the "startup stage" (Model 1: beta = 1.136, p = .036) in comparison to the "early stage" (Model 2: beta = 0.350, p = .201) and "later stage" categories (Model 3: beta = 0.361, p = .070).

The second situation concerns cases where the startup has an affiliation with a prominent IVC. Affiliation with a prominent IVC can be interpreted as a strong quality signal for other investors (Hsu, 2006; Stuart et al., 1999), leading to less information asymmetries. In addition, this affiliation provides social defenses against misappropriation risks and facilitates information release by the startup (Colombo & Shafi, 2016; Hallen, Katila, & Rosenberger, 2014). This is not only because CVCs intend to maintain favorable ties with IVCs as desirable future partners (Burt, 2005), but also because prominent IVCs can leverage their positions to effectively broadcast and punish the alleged misbehavior by CVCs (Hallen et al., 2014). Accordingly, we expect public disclosure to have a weaker effect in the above cases, since the information was largely available pre-AIPA for evaluating the quality of these startups. We define prominent IVCs based on whether they are in the top decile of eigenvector centrality. Eigenvector centrality is measured based on the syndication network of prior five years (Hochberg, Ljungqvist, & Lu, 2007). The results (Table 3, Models 4 and 5) show that AIPA significantly increases the probability of CVC investment for startups that are *not* associated with prominent IVCs (Model 4: beta = 0.583, p = .001). We do not find similar results for startups that are associated with prominent IVCs (Model 5: beta = 0.237, p = .522).[16]

For the third case, we consider startups that formed investment relations with CVCs in the past. This relation can also serve as a quality signal (similar to affiliation with a prominent IVC). Especially since CVCs—as technology experts—have vetted the quality of the startup (Maula, Autio, & Murray, 2005). Moreover, it implies that startups have already revealed technological information to a CVC in prior rounds. Since the level of information asymmetry is lower in the following rounds of collaboration between a startup and a CVC, we expect that search costs would be

TABLE 3 Columns 1–3 report the impact of AIPA on receiving CVC investments for startups in the startup stage (model 1), early stage (model 2), and later stage (model 3)

Sample	(1) Startup stage	(2) Early stage	(3) Later stage	(4) Without prominent IVC	(5) With prominent IVC	(6) Without prior CVC	(7) With prior CVC
Biotech	−0.464	−0.068	−0.054	−0.067	−0.251	−0.231*	0.234
	(0.399)	(0.211)	(0.174)	(0.152)	(0.330)	(0.123)	(0.303)
Post-AIPA × biotech	1.136**	0.353	0.361*	0.583***	0.237	0.577***	0.195
	(0.543)	(0.274)	(0.196)	(0.177)	(0.371)	(0.158)	(0.322)
Round number (ln)	0.042	−0.002	−0.045	0.017	−0.322**	−0.394***	−0.907***
	(0.197)	(0.103)	(0.061)	(0.062)	(0.141)	(0.058)	(0.146)
Share CVC deal flow	1.434	5.371*	4.662***	4.046***	5.732*	6.003***	1.236
	(4.539)	(2.776)	(1.418)	(1.364)	(3.299)	(1.653)	(2.031)
IVC per venture	5.595	−3.079	−4.786	−6.282*	0.798	−7.589*	−3.598
	(13.411)	(6.240)	(3.168)	(3.274)	(5.315)	(3.981)	(4.702)
Syndication size	0.437***	0.379***	0.324***	0.340***	0.291***	0.323***	0.333***
	(0.064)	(0.030)	(0.016)	(0.017)	(0.025)	(0.016)	(0.027)
California	−0.228	0.220*	0.142*	0.154*	0.019	0.272***	−0.258*
	(0.225)	(0.117)	(0.085)	(0.079)	(0.140)	(0.067)	(0.137)
Massachusetts	−0.273	−0.002	−0.119	−0.084	−0.215	0.053	−0.596***
	(0.393)	(0.175)	(0.115)	(0.112)	(0.196)	(0.096)	(0.187)
Nasdaq	2.376	2.030	−2.095	−1.174	−0.938	−0.340	−1.020
	(5.209)	(2.662)	(1.294)	(1.334)	(2.324)	(1.667)	(1.846)
N	1,271	3,618	8,814	11,378	2,325	11,258	2,445
No. startups	988	2,673	3,621	4,730	1,267	4,899	978
Chi-square (*p* value)	.000	.000	.000	.000	.000	.000	.000

Notes: Columns 4 and 5 include startups without prominent IVC (model 4) and with prominent IVC (model 5). Similarly, models 6 and 7 include startups without prior CVC investment (model 6) and with no prior CVC investment (model 7). Dependent variable is "Deal CVC." The benchmark group is US software VC backed startups. In all models, clustered robust standard error is reported in parentheses; *, **, or *** indicate statistical significance at the 10, 5, and 1% level, respectively. All models include year and stage of development fixed effect.

lower for startups that have formed investment relations with CVCs in the past. The results (Table 3, Models 6 and 7) show that AIPA significantly increases the probability of CVC investments for startups that have not received prior CVC investments (Model 6: beta = 0.577, p = .000). However, we do not find similar results for startups that received prior CVC investments (Model 7: beta = 0.195, p = .544). The presented analyses show that AIPA is more effective where search costs and information constraints are higher, which provides support for the supply-side theoretical mechanism.

6.2.2 | Hazard of investment

Lower search costs on the supply side predict that CVCs will detect and evaluate startups easier and will thus make faster investment decisions. Competition between CVCs may also arise after AIPA, which may have driven faster investment decisions. Startups on the other hand, having their technology disclosed without a guarantee for IP protection, are more prone to misappropriation. Thus, they would prefer earlier CVC relations to protect their technology from other corporations. Both mechanisms would imply that the hazard (timing) of the CVC–startup relationship improves post-AIPA. To test for this, we consider the time to form an investment relationship as the dependent variable and estimate a Cox proportional hazards model. We measure time to CVC investment using two different timing variables. We use the round number (Table 4, Model 1) and number of days from the first round of investment (Table 4, Model 2) as the dependent variables. Using both measures, we obtain positive and significant coefficients (Model 2: beta = 0.615, p = .000; Model 3: beta = 0.730, p = .000) implying that AIPA increases the hazard rate of CVC investments. This is also consistent with the results in Column 1 of Table 3 that demonstrates that after AIPA, CVC investments are more likely to happen in early stage startups. The results of these tests are consistent with both theoretical mechanisms (demand side and supply side) discussed above.

6.2.3 | Startup valuation

As the last set of analyses, we run a test to check the demand-side mechanism. This mechanism would predict that after AIPA, startups would rush to collaborate with CVCs to protect their technology via the complementary resources of the corporates. They may also do so because after a public disclosure, the competitive advantage of their technology may gradually diminish. This perspective implies higher demand to form investment relationships from the startups' side. Accordingly, AIPA should reduce startups' bargaining power. As a direct consequence of this mechanism, we would expect to observe lower valuations and investments from CVCs in the post-AIPA period. To check for this effect, we estimate our model for all startups that received CVC investment, employing *pre-money valuation* and *investment size* as the dependent variables.[17] Contrary to these predictions, the results (Table 4, Columns 3 and 4) show that after AIPA, CVC-backed startups in the biotech industry received significantly higher valuations (Model 3: beta = 0.352, p = .024) and a larger amount of investments (Model 4: beta = 0.484, p = .000) relative to software startups.[18] These findings suggest that better matches occurred after AIPA, which is more consistent with the supply-side mechanism (friction reduction) than the demand-side mechanism.

We acknowledge that these mechanism tests are imperfect and cannot indicate a definitive theoretical channel for AIPA. Yet, the analyses overall provide suggestive evidence for a more significant effect through the search-cost reduction mechanism on the supply side.

6.3 | Additional analysis

In the main analyses, we use US software as the benchmark group. As a complementary analysis, we use Europe-based biotech startups as the alternative benchmark. A key motivation for using alternative benchmarks is to create an opportunity to test the validity of our assumptions. The implicit assumption here is that the effect of AIPA is almost irrelevant for the benchmark groups. If this statement is correct, then we should not observe a strong effect across the benchmarks—see the table in Appendix S4.

To start, we first report the main results using EU biotech as the benchmark. Due to data quality concerns, we limit the European countries to the United Kingdom, Germany, France, and Sweden, which together comprised more than 70% of investment rounds in Europe. The univariate analysis (Appendix S5) illustrates that after AIPA, the likelihood of CVC investment increases by around 12.1% for US biotech startups, relative to EU biotech startups. In Appendix S6, we report the multivariate analyses. The results in Column 2 are consistent with the univariate analysis and show that after AIPA, CVC investment in US-based biotech increase relative to EU-based biotech startups (Model 2: beta = 0.517, p = .064). The coefficients imply that due to AIPA, the probability of CVC investment for US-based biotech startups increases by 6.5% (33.8% of the mean of sample) relative to EU-based startups. Using the second benchmark requires a strong assumption. The assumption is that startups in each geographical location (US

TABLE 4 Model 1 and 2 reports cox proportional hazard model of CVC investment

Dep. var.	Cox proportional hazard model (1) Investment timing (rounds)	Cox proportional hazard model (2) Investment timing (days)	OLS (3) Valuation (ln)	OLS (4) Round size (ln)
Biotech	−0.332***	−0.604***	0.015	−0.148
	(0.108)	(0.126)	(0.116)	(0.114)
Post-AIPA × biotech	0.615***	0.730***	0.352**	0.484***
	(0.123)	(0.145)	(0.156)	(0.123)
Controls	Yes	Yes	Yes	Yes
N	13,703	13,703	1,130	2,562
No. startups	4,957	4,957	749	1,497
Log likelihood	−21,423.2	−73,782.5		
R square			0.407	0.377
Chi-square (*p* value)	.000	.000	.000	.000

Notes: Timing is measured based on the round of investment (model 1), and based on the number of days since first round of investment (model 2). Model 3 and 4 reports OLS regression of effect of AIPA on pre-money valuation at the round of investment (model 3), and amount of investment (4) in CVC backed startups (Deal CVC = 1). Our sample is smaller for pre-money valuation, since SDC platinum report the valuation for only 44% of rounds of investments in our sample. In all models, clustered robust standard error is reported in parentheses; *, **, or *** indicate statistical significance at the 10, 5, and 1% level, respectively. All models include all control variables: Round number (only in columns 3 and 4), Share CVC deal flow, IVC per Venture, Syndication size, California, Massachusetts, Nasdaq, year fixed effect and stage of development fixed effect.

and Europe) are more likely to file their patents first in their closest patent office (country or EPO in the case of EU-based startups, and the USPTO in the case of US-based startups).

Next, we test the implicit assumption behind the choice of benchmarks. To do so, we run several placebo tests, comparing the effect across our benchmarks. Benchmarks here are related to Geography (EU-based) or Industry (Software). Column 3 (US software vs. EU biotech), Column 4 (US software vs. EU software), and Column 5 (EU biotech vs. EU software) in Appendix S6 show the results for different combinations of benchmark groups. The placebo tests demonstrate that there is no statistically significant effect of AIPA across our benchmark groups (Model 3: beta = −0.002, $p = .995$; Model 4: beta = −0.079, $p = .762$; Model 5: beta = −0.380, $p = .223$), which confirms the validity of our empirical approach. Model 3 is especially important because if the results in Table 2, Model 1 are driven by the impact of the dot-com bubble on software startups (our first benchmark group) instead of by AIPA, then the effect should be observed in this model as well. However, the estimated effect is almost equal to zero.

In addition to the aforementioned analysis, we conducted one more robustness check to test the validity of our identification strategy and to confirm that the observed effect is due to AIPA. We run a *falsification test* by repeating our quasi-natural analysis on a 10-year pre-policy change sample (1990–1999). We assume the middle of the period as the time at which a *fake* policy change happened (Post-AIPA-fake) and estimate Equation (1) using both our benchmark samples. We would expect not to observe any similar effects as the real policy change in our analysis. The results (Appendix S7) show that the effect is not statistically significant from zero, supporting our main analysis.

Table 5 provides a summary of all empirical concerns about our results and corresponding analyses aimed at alleviating these concerns.

7 | CONCLUSION AND DISCUSSION

This study aims to investigate the effect of patent disclosure through AIPA—as one of the most significant amendments to the US patent system—on the venture financing market. We show that the pre-grant public disclosure

TABLE 5 Summary of robustness tests and additional analyses described in the paper

Panel A: Addressed concerns	
Concern	**Solution**
A1. Can industry-specific shocks and contaminations (especially the "dot-com bubble") explain the observed pattern in the data?	This concern is addressed in two ways. First, the analysis reported in Table 2 (column 6 and column 7) should alleviate this concern. Since we compare startups within the same industry (biotech or software). Here again we can see a strong and positive effect for biotech startups but not for software startups. Second, we used the second benchmark group (EU biotech) versus US biotech. While the dot-com bubble affected the software sector (our first benchmark group), it had no significant effect on VC investments in biotech startups. Hence, this analysis alleviates the concern regarding the confounding effect of the dot-com bubble (Appendix S6, model 2). Moreover, if our results are driven due to the impact of dot-com bubble on software startups (our first benchmark group) and not AIPA, the effect should also be observed on our placebo tests comparing EU biotech startups with US software startups. The results show that effect is not statistically significant and coefficient is close to zero (Appendix S6, model 3: $b = -0.002$, $p = .995$).
A2. Is US software a good benchmark for US biotech? If AIPA affects software startups, this sample would not be a good benchmark.	We have reported several alternative benchmarks in our empirical analyses with consistent results. However, to check this issue, we rely on the results reported in Table 2 (Column 6 and 7). The results compare biotech and software startups that applied for a patent before vs. after AIPA. For the biotech sample, startups applying for patents after AIPA are more likely to receive CVC investments (relative to startups that applied for a patent before AIPA). However, we do not observe such an effect for the software sample. This provides evidences that the effect of AIPA is smaller (or insignificant) on software startups. Such a benchmark is also used in the prior literature (e.g., Mann & Sager, 2007). Finally, if AIPA affects the software sample in a similar fashion, it would create a bias against our findings. Thus, the selection of software is a conservative choice for our empirical analysis.
A3. Is it possible that the result is driven by IVC reduction rather than CVCs investments? One might argue that CVCs in the treatment (US biotech) and first benchmark group (US software) remain relatively stable in their sector before and after AIPA—while IVCs shift more easily between sectors. Hence, observed effect is due to lower IVC activities.	The analysis comparing the second benchmark group (EU biotech), which is in the same industry of the treatment group (US biotech), should alleviate this concern. We further control for the number of active IVCs relative to the number of startups in the industry and year (IVC per venture) in all specifications. Alternatively, in an unreported analysis we also controlled for number of unique IVCs that invested in the industry and region of startup in the focal year. These control variables can capture the changes in IVC pattern of investment.
A4. Do startups in the sample differ systematically pre and post AIPA?	We repeat our analysis on a subsample of startups that received at least one round of investment before and one round after AIPA. This setting ensures having the same set of startups pre/post AIPA in the analysis, which allows us to include startup fixed effects in the model. The results (Table 2, model 2) remain very similar. We also address this concern by matching each observation post-AIPA to one observation pre-AIPA using propensity score matching (Table 2, model 3). The results are very similar to the main analysis.

(Continues)

TABLE 5 (Continued)

Panel A: Addressed concerns	
Concern	**Solution**
A5. Can the public disclosure due to AIPA lead to lower bargaining power for startups investment relations with CVCs.	Our results (Table 4, columns 3, 4, and 5) do not support this explanation. This concern would imply startups receiving lower valuation and investment size form CVCs. Yet, we show that after disclosure, startups that form investment relations get higher valuations (column 3), receive larger investment (column 4) and there is no statistically significant effect on their successful exit (column 5).
Panel B: Additional analyses	
Test	**Result**
B1. Placebo analysis on the pre-event period.	We run a falsification test, by repeating our quasi-natural analysis on a 10-year pre-policy change sample (1990–1999). We assume the middle of the period as the time that a fake policy change happened (Post-AIPA-fake) and estimate Equation (1) using our both benchmark groups. We would expect not to observe any similar effects as the real policy change in our analysis. The result (Appendix S7) shows that the effect is not statistically significant from zero, supporting our main analysis.
B2. Placebo analysis between benchmark groups (US software vs. EU biotech).	We introduce the benchmark groups as samples where AIPA has small effect (on our dependent variable). Therefore, we expect not to find a significant result of AIPA across these samples. The placebo test (Appendix S6, model 3) shows that there is no statistically significant effect of AIPA between our main benchmark groups, (model 5: beta = –0.002, p = .995).
B3. Placebo analysis in software (US software vs. EU software).	We argued that AIPA does not have a significant effect in software industry. To test this, Appendix S6, model 4 compares software VC-backed startups in the US with Europe. The placebo test shows that there is no statistically significant effect of AIPA in software (model 4: beta = –0.079, p = .762).
B4. Placebo analysis in EU (EU biotech vs. EU software).	As we argued, AIPA was only enacted in the US, thus we do not expect to find an effect for the EU sample. Appendix S6, model 5 compares EU biotech with EU software VC-backed startups. The placebo test shows that there is no statistically significant effect of AIPA in EU sample (model 3: beta = –0.380, p = .223).

effect of AIPA increases the likelihood of CVC investment in startups in industries where patents are more relevant (namely, biotech compared to software). Our analyses suggest that the effect occurs mainly through friction and search-cost reduction mechanisms on the supply side, and not because of the lower bargaining power of startups post-AIPA. Below, we discuss a few implications of this study.

First, our results underscore the role of the mandatory disclosure function of IP systems for startups' access to resources. The literature has already established the role of stronger IP regimes in facilitating CVC investments (see, e.g., Dushnitsky, 2006, Dushnitsky & Shaver, 2009, Katila et al., 2008). Our study complements this strand of literature by focusing on a special case of disclosure through AIPA—which is public, mandatory, pre-grant, and verifiable. Moreover, the literature does not directly observe startups' disclosure decisions and presumes they are a consequence of strong defense mechanisms. Our study directly observes a public disclosure shock resulting from an institutional reform and analyzes its effects on startup financing. Finally, regarding the role of IP regimes on the CVC–startup relationship, the literature primarily focuses on the *protection* function and its consequent effects (see e.g., Dushnitsky & Shaver, 2009). Our work is among the few studies to directly analyze the *disclosure* function of IP systems, as well as its impact on the formation of the CVC–startup relationship.

Second, we highlight the hindering effect of frictions and information constraints on the market for venture financing. By showing that early public disclosure through AIPA facilitates the formation of the CVC–startup investment relationship, we provide policy and market design implications for promoting technology entrepreneurship. These findings also point to potential losses caused by market frictions; CVCs have advantages for nurturing technology startups due to their complementary and nonfinancial resources (Alvarez-Garrido & Dushnitsky, 2016; Chemmanur et al., 2014). Despite this, their market share does not reflect such advantages. One common view is that rampant information constraints on CVCs make such advantages ineffective (Dushnitsky & Shaver, 2009). Our study provides evidence to support this view by showing that AIPA improves CVC–startup investment relations—and does it more effectively in environments where information constraints are stronger. Increasing the likelihood, valuation, and round size, we find no evidence that the investment relationship post-AIPA harms startups. This provides supportive evidence that a transparent information environment can facilitate ties, which are essential for startups' growth and success.

Finally, and related to the above, our work connects to the policy debates and concerns related to the adverse effect of AIPA on small and independent inventors. The mandatory disclosure provision has been at the center of these debates (see, e.g., Barich, 2001; Ergenzinger, 2006; Gallini, 2002; Modigliani, 1999). Our results highlight one aspect of the complex corporate–startup relation in the wake of AIPA reform and show that the new law, while generating serious misappropriation concerns for startups, may facilitate their access to valuable corporate assets. Of course, we cannot make welfare statements from our findings; this would require more rich CVC-level data—regarding their investment payoff—and the calculation of the overall effect of AIPA. Until then, these issues remain a topic for future research agendas to address.

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ENDNOTES

[1] Under certain conditions, US patent applicants could still opt out of AIPA coverage and demand secrecy by submitting a request to the United States Patent and Trademark Office (USPTO) any time before 18 months from the application date. However, Graham and Hegde (2015) show that very few patent applicants (less than 7%) opted out of the pre-grant disclosure. Similar to Hegde and Luo (2017), in our analysis, we ignore the opt-out provision.

[2] Besides the mandatory 18-month disclosure, AIPA also implemented small changes to the provisional royalty rights and patent term guarantee. However, the literature related to AIPA consistently focuses on the 18-month disclosure provision as the key change, while the other changes are considered minor (see, e.g., Barich, 2001; Hegde & Luo, 2017).

[3] After AIPA, disclosed inventions are conveniently searchable and accessible via the USPTO webpage (https://www.uspto.gov/patents-application-process/search-patents)

[4] US patent law generally allows for a maximum 12-month grace period. This implies that any invention publicly disclosed beyond this period is not patentable, as it is regarded as prior art.

[5] Alvarez-Garrido and Dushnitsky (2016) reported a relevant anecdotal quote from an entrepreneur: "Pfizer really showed us they know this space. They know how to design clinical trials here, and they know ophthalmics not only clinically but from the sales and marketing side. They were hands down the best partner we can possibly find here" (p. 822).

[6] One may also argue that—given the disclosure risks after AIPA—startups with high-potential technologies may no longer use the patent system. While this is theoretically possible, research has not found a significant difference in the patent characteristics before and after AIPA (Baruffaldi & Simeth, 2020). We also tested for this effect in our study sample and found no significant difference between startups' patents before and after AIPA—these results are available upon request.

[7] Accordingly, several legal scholars have argued that software patents might not satisfy the sufficient disclosure requirement of the patent law (see e.g., Cohen & Lemley, 2001). This is in contrast with biotech patents, which have to disclose much more detailed information in patent documents rather than giving a generalized description of the invention (Naini, 2004).

[8] The within-industry analyses are instrumental for the conclusions we make in this study, as they isolate other industry-specific factors. For instance, the importance of founders' tacit knowledge about startup's technology (Paik & Woo, 2017) is a factor which differs across industries and could motivate the formation of investment relationships. Our within-industry analyses present the net effect of disclosure, by muting such relevant industry-specific factors.

[9] Other investor types are individuals, angel groups, banks, government-affiliated institutes, among others. IVCs and CVCs represent more than 78% of all the investors. In addition, 95.8% of all high-tech startup deals include at least one IVC or CVC.

[10] http://www.patentsview.org/web/#viz/relationships

[11] http://funginstitute.berkeley.edu/research/innovation-in-tech/tools-and-data/

[12] The choice of a 2-year time window is motivated by sample size considerations. Restricting the sample to a 6-month or 1-year time window would have generated a very small samples, such that a meaningful statistical analysis would not be feasible (the number of observations for biotech startups for the 6-month and 1-year samples are 28 and 73, respectively).

[13] Equation (1) is only used for a representation of our empirical model and does not intend to show the Logit specification.

[14] We cannot estimate θ_2 due to collinearity with year fixed effects.

[15] In Appendix S3, we repeated this analysis on the fixed effect sample, which allows us to include firm fixed effect.

[16] Alternatively, we define IVCs in the top quintile of eigenvector centrality as a prominent IVC and find very similar results.

[17] Our sample is smaller for pre-money valuation, since SDC Platinum reports the valuation for only 44% of rounds of investments in our sample.

[18] While we focus on the positive effect of AIPA in receiving investments as *inputs*, one may wonder whether information of an investment relation after AIPA came at the cost of worsening the *outcome* for startups. To check for this, we consider an outcome proxy, namely startups' successful exit. If CVCs' main objective is to misappropriate the technology, and public disclosure reduces the bargaining power of startups, we should observe a lower likelihood of successful exits after AIPA. The results shows that AIPA has a positive but statistically insignificant effect on the successful exit of startups (beta = 0.307, p = 0.284). This implies that CVC investments after AIPA did not worsen the outcome situation for startups, which also does not support the loss of the bargaining power mechanism. The analyses are available upon request.

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