The Acquisition Option and Startup Innovations

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Abstract

I study a novel channel affecting startup innovations: how acquisition and venture capital markets shape startups' innovation incentives. A startup's catering incentives increase as an exit through acquisition becomes relatively more attractive. My theoretical framework demonstrates that as the availability of venture capital increases, startups' catering incentives decrease. To provide evidence of this channel, I develop novel text-based measures suitable for measuring changes in the direction and complementarity of startups' innovations, thereby expanding the scope of innovation activity studied in prior literature. Startups innovate more in directions with high acquisition activity, and following an exogenous increase in local capital supply, startups introduce innovations that are more independent of potential acquirers' assets. Overall, my results suggest that the availability of external financing is key to understanding startup firms' innovation incentives and, ultimately, innovation output.

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1 Introduction

Young high-growth firms contribute disproportionately to innovation output as well as economic and productivity growth.[1] Many of these firms depend on external financing and turn to venture capital (VC) markets. A key feature of the VC market is the importance of a timely exit through which investors and entrepreneurs can realize their investment, most commonly through an initial public offering (IPO) or a trade sale. The importance of the exit event is driven by the VC funds' fixed investment horizons and the lack of liquidity in the secondary market for investments in private companies. Despite the important contribution to innovation output by VC-financed firms and the importance of the exit event in determining entrepreneurs' and investors' payoffs, research on the role of exit markets in shaping the path of innovation is scarce.

This paper studies how the prospects of a future exit shape the innovation incentives and output of startups. I construct novel text-based measures suitable for measuring the direction of startup firms' innovations and their relation and level of complementarity to incumbent firms' assets. A larger share of startup firms' innovation activities can be studied by complementing the patent data with trademarks.[2] The empirical evidence shows that startup firms innovate more in areas with active acquisition markets, suggesting that the acquisition motive shapes the startup firms' innovation incentives. When the catering incentives are weaker, as an exit by acquisition becomes relatively less attractive, startup firms introduce innovations that are more independent of potential acquirers' assets. I develop a theoretical framework that rationalizes these findings, highlights the role of VC markets in shaping the catering incentives, and generates testable predictions. To provide causal evidence of the role VC markets play in shaping the startup firms' catering incentives, I use the staggered implementation of the Prudent Person Rules (PPR) across US states as a source of exogenous variation in local VC supply. The innovation strategies of startup firms that experienced increased VC supply became more independent of potential acquirers' assets relative to startup firms not experiencing the increase.

Incumbents have a disincentive to innovate in a direction that cannibalizes their market share and makes their assets obsolete (e.g., Arrow, 1962), creating a key economic role for new firm entry in driving technological advancements and growth (e.g., Schumpeter, 1942). When a startup firm is anticipating an acquisition, its innovation incentives should align with the potential acquirer

[1] See, e.g., Chava, Oettl, Subramanian and Subramanian (2013) and Haltiwanger, Jarmin and Miranda (2013).

[2] Previous literature in economics and finance has primarily focused on patent data. The trademark data make it possible to measure the direction of innovation activity of a larger share of firms, including those firms with innovations that are not patentable.

to maximize its expected exit value. The direction of innovations should change to become more complementary to the incumbents' assets. The startup firm incorporates the potential acquirers' disincentive to innovate if the relative importance of an exit by acquisition increases. Conversely, the startups' innovation strategy should be less directed toward existing assets in the market if the relative expected value of staying independent and possibly going public increases. However, I argue that new firms, both those anticipating an exit through acquisition and those that remain independent, have an incentive to cater but that the trade-off depends on market characteristics. The types of innovations that eventually reach the market becomes, on aggregate, more similar to incumbents' assets when firms strategically cater.

The catering motive influences the innovation strategy of startup firms, and the relative supply of VC determines to what extent the catering motives influence the innovation strategy of startups. Firms innovate more in directions where acquisition markets are more attractive. However, the incentive to cater to prospective acquirers is weaker when capital supply is high. When capital supply, or equivalently competition in the VC markets, is higher, firms can raise capital more readily and at more favorable terms, increasing the relative value of staying independent. The innovating firm faces a trade-off between maximizing the value as an independent firm or as an acquired entity, and the extent to which startup firms cater to potential acquirers depends on VC market competition.

The theoretical framework formalizes this economic mechanism. I build on a model of search commonly used in the labor literature and applied to the startup and VC market by Inderst and Müller (2004) and Michelacci and Suarez (2004).[3] I extend this type of model to illustrate how acquisition markets and VC markets jointly shape the startup firms' innovation incentives by introducing two possible exit paths and a decision on the direction of innovation by the startup firms' owners.[4]

One insight from the model is that complementary innovations benefit the current owners of the startup in the event of an acquisition and through an improved bargaining position when raising additional external capital. A decrease in capital supply increases the incentive to cater to potential acquirers through two channels. First, an exit through an acquisition becomes relatively more attractive as the expected value of staying independent decreases. Second, the

[3]See, e.g., Pissarides (2000) for applications of search models in the labor literature.

[4]Dijk, Moraga-González and Motchenkova (2021) develop a model to study how startups strategically cater to incumbents to increase expected acquisition rents and the implications on social welfare. Instead, this paper documents the role of financial markets in shaping these incentives.

startup's owners' incentive to improve their bargaining position increases.

The empirical analysis has three building blocks and uses four primary data sources. First, I construct novel text-based measures suitable for measuring the direction and level of complementarity of startups innovations. Second, with these measures, I construct the startups' *innovation networks* and study how the evolution of the networks relates to the relative attractiveness of the acquisition markets. Last, I exploit the staggered implementation of the Prudent Person Rule to show that startup firms catering incentives are weakened by an increase in VC supply, which translates into more independent innovations. The analysis uses a sample of VC-financed firms from Venturexpert. The sample includes all firms based in the US, founded after 1980, that at some point have received VC financing. The US VC market is a suitable laboratory with a large sample of firms subject to similar regulations. Their intellectual property—patents and trademarks—are available from the US Patent and Trademark Office (USPTO). Moreover, these firms primarily do business in the US, and most potential acquirers are located in the US.[5] I match the Venturexpert sample of startup firms to the USPTO Trademark Case File data set and patent data from the USPTO Bulk Data Storage. Lastly, all public US firms in Compustat serve as a proxy for the set of potential acquirers.

Commonly used innovation measures such as patent counts and citation-based measures (e.g., forward and backward citation counts) are informative about the effectiveness and impact of a firm's innovation strategy. However, they offer limited insight into the direction and content of innovations and their relation to other firms' assets. Other patent-based measures that look at cross-citations or other proxies of overlap can be informative about the relation of a startup's technological innovations to incumbent firms' assets. However, many novelties and innovations introduced by startup firms are not patentable. A firm's innovations encompass many activities, including technological innovations and product enhancements, process improvements, and new business models. The trademark data widens the scope of innovative activities—new firms are often innovative along dimensions not captured by patents and thus complement the patent data. From the trademark filings, I obtain a description of a firm's goods and services and the date of first use in commerce. The description identifies in which areas a firm is operating and the evolution of the scope of the firm's business. By using trademarks, I study firms in industries that

[5]For example, a similar study of startup firms in a European country would result in a much smaller sample of firms. Patents and trademarks might only be available through the domestic patent office in the local language or through the European Patent Office in English. Lastly, the set of potential acquirers most likely extend beyond the country's borders. Implementing the empirical strategy in this paper would thus require an international sample of potential acquirers matched to several different IP data sources with local variations in the standardization of application procedures and language, hence why the more straightforward US setting is used in this paper.

are typically not patent-intensive (e.g., retail) and capture innovations that are not patentable also in industries with many patents (e.g., computer software).[6] Patents instead describe the details of a firm's technological innovation output.

I study the startups' patents and trademarks, including both the evolution of their *innovation portfolios* and their new *introductions*. A firm's portfolio consists of all patents or trademarks owned (the stock), while introductions include the new additions in a year (the flows). I construct panels of word vectors representing the patents and trademarks of the startup firms and potential acquirers for both the portfolio and the introductions. The innovation overlap between the startup and potential acquirers is then represented by the cosine similarity of the two text corpora, comparing portfolio-to-portfolio or introductions-to-portfolio. The cosine similarity is a common measure for comparing textual similarity, and within the finance literature, cosine similarity has been used by, e.g., Hoberg and Phillips (2010). I compute the similarity score between each startup and potential acquirer by year and obtain a large (unbalanced) panel of startup-potential acquirer pair observations.

The measures I construct are motivated by the large literature on the determinants of the probability and success of merger and acquisition activity. The first strand of literature suggests mergers are primarily motivated by complementarities; asset complementarities determine incidence and value of acquisition (e.g., Rhodes-Kropf and Robinson, 2008) and the property rights theory suggests these synergies are most effectively realized when assets are under shared control (e.g., Grossman and Hart, 1986; Hart and Moore, 1990). Complementarities arising from innovation activities as determinants of acquisitions have been documented by, e.g., Hoberg and Phillips (2010) and Bena and Li (2014). A different view emphasizes the incumbent firms' incentives to escape competition and increase market power (e.g., Cunningham, Ederer and Ma, 2021; Baker and Bresnahan, 1985).[7] While both motives are likely to be present in the data; both also suggest some degree of overlap between the targets' and the acquirers' innovation activities, e.g., firms buy similar firms. The measures capture the similarity or overlap in innovation activities that motivate acquisitions, regardless of whether acquisitions are driven primarily by complementary

[6] For example, the biotechnology and electrical component industries are patent-intensive, while many innovations in the retail and computer software sector are not patentable. I show that the sample of firms with a trademark is more representative of the full sample of VC-financed firms. About 55% of firms in the sample have at least one trademark, while only 22% have a patent. Among firms with a patent, more than 80% have at least one trademark.

[7] Antitrust authorities' scrutiny of merger and acquisition activity primarily focuses on the competitive implication of such activity. Recently, the high acquisition activity of young, small firms by large technological incumbents has been under regulatory scrutiny. This paper instead documents the implications on startup firms' ex-ante innovation decisions.

or anticompetitive motives.

The panel of similarity scores is akin to a network structure where potential acquirers and startups are nodes. The similarity score measures the strength of the connections between each startup and potential acquirer. The measures represent how each startup's innovation strategy evolves, allowing me to observe how the ties to potential acquirers change after the startup makes a new introduction. If the startup's new introduction overlaps with the potential acquirer's existing assets, the strength of the connection measure increases, indicating that the startup gravitates closer toward the potential acquirer.

The first set of empirical results show that startup firms are more likely to innovate *toward* an area where acquisition activity is higher, suggesting that acquisition activity is an important factor in determining the direction of innovation. I measure acquisition activity as the three-year lagged average of acquisitions of other startups closely related to the potential acquirer. The results suggest a 2–4% higher similarity score, relative to the mean score, in new introductions for a one standard deviation increase in the acquisition activity measure. The corresponding estimate is about 0.5–1% at the portfolio level. However, the average difference in the acquisition activity measure across the closely related acquirers within each startup-year observation is almost twice as large as the sample standard deviation. The acquisition motive is an important determinant of startup firms' innovation strategies, as the estimates are economically and statistically significant.

In these tests, I estimate the relative strength of the directional effort across a plausibly relevant set of directions for a given startup firm. Each specification includes startup and year fixed effects or startup-year fixed effects. The fixed effects control for the startup's inherent propensity to produce innovations similar to incumbents, and the estimates instead show the relative propensity to exert innovative efforts in different directions with different acquisition histories. The startup's actions drive the directional results as I only consider observations immediately after an introduction by the startup firm and compare the new introduction and resulting portfolio to the incumbents' assets prior to the new introduction. However, acquisition activity probably correlates with demand for the type of assets in an area, suggesting that startups are more likely to innovate in a given direction because good investment opportunities correlate with high acquisition activity. Therefore, these results are complemented with a natural experiment to address the endogeneity concerns and address the question: Do startup firms introduce less independent innovations when catering incentives are stronger?

In the second set of empirical results, I exploit a plausibly exogenous variation in local capital inflows to identify the causal effect on the firms' incentive to engage in complementary innovations—the staggered implementation of the PPR across US states. State pension funds not covered by the Employee Retirement Security Act were allowed to invest in alternative assets classes such as private equity and VC funds after the adoption of the policy by their home state. Previously such investments were excluded from portfolio inclusion. In line with González-Uribe (2020), I show that inflows into the local state VC markets increased significantly post-adoption, compared to other funds located in states that did not adopt the legislation in the event window. Moreover, this disproportionately increased inflows into local startups relative to startups located in non-adopting states.

I estimate a stacked difference-in-differences model where "treated" startups are located in a state that adopts the PPR. The control group consists of firms in the same industry but in a different state that did not adopt the legislation over a specified time window. By using the stacked approach, I control the construction of the control group. I report the inclusion criteria for the control group in conjunction with all results, thus highlighting how different criteria might drive the results. Moreover, the stacked approach is suitable when estimating the average treatment effect on the treated group in a staggered difference-in-difference framework in the presence of heterogeneous treatment effects, which is of concern in this setting given the varying size and structure of the VC market across industries and states.[8] Lastly, the panel data is highly unbalanced, and the stacked approach is suitable when dealing with such data.

The results show a statistically significant decrease in the level of complementary innovations following the adoption of the legislation, suggesting that as the relative value of the acquisition option decreases, startup firms engage in less complementary innovations. The results suggest an average treatment effect of 0.3 to 0.5 and 0.8 to 0.85 lower similarity scores, corresponding to about a 2 and 4.5% lower score relative to the sample mean for the trademark and patent sample, respectively. These results support the economic mechanism outlined in the theoretical framework. The specification addresses the primary empirical challenge; omitted factors are unlikely to drive the changes in the startups' direction of innovation and complementarity. Increased demand or good investment opportunities are unlikely to correlate with the timing of PPR adoption but are plausibly correlated with both innovation and acquisition activity as well as VC investments.

[8] See, e.g., Baker, Larcker and Wang (2021).

The adoption of the policy in each state would have to coincide with changes in such opportunities across treated and non-treated startups in different states but in the same industry to invalidate the identification strategy. Moreover, increased demand and opportunity growth should benefit investors and stimulate fund flows, and an increase in demand should stimulate innovation in the area regardless of conditions in the exit markets. If firms can more easily raise capital, they should be more likely to invest more to grow in high-demand areas. If it is variation in underlying demand driving the results and not acquisition incentives, the complementary innovation measures should, if anything, increase in capital supply, not decrease. Second, an increase in demand should stimulate general innovation within the area, not necessarily the degree to which firms engage in complementary innovation efforts.

In contrast, this paper theoretically motivates and empirically documents a different channel with the opposite predictions. A general increase in demand followed by increased acquisition activity and valuations stimulate both VC entry and entrepreneurial entry. However, an increase in capital market competition should decrease the *startup's owners'* incentives to adjust their innovation strategy to cater to incumbents.

This paper contributes to the understanding of the determinants of startups' innovation incentives. Specifically, it focuses on the incentives to cater to potential acquirers and the role of VC markets in shaping these incentives. I document a novel channel with potential long-term implications on the economy, relevant to innovation policy and antitrust policy. The results show that catering incentives are an important factor shaping startups' innovation policies. These incentives are weaker when staying independent is relatively more attractive, and capital supply is relatively higher. Last, the innovation measures developed for this paper are useful for addressing other questions where the direction and scope of startups innovations are of interest. Moreover, by complementing the patent data with trademarks, a larger share of innovation activity can be studied.

2 Related Literature

This paper contributes to several strands of literature. First, the paper closest to the current study is Wang (2018), which is, to my knowledge, the only other paper to study the catering motives of startup firms empirically. She studies how incumbents' market structure affects entrepreneurial entry and the catering conditional on entry. However, it is unclear whether active acquisition markets deter entry, as acquisition activity can also be high in segmented markets. Some evidence suggests that acquisition activity stimulates VC entry (e.g., Phillips and Zhdanov, 2017) and innovation activity by small firms (e.g., Phillips and Zhdanov, 2013; Caskurlu, 2019). Nanda and Rhodes-Kropf (2013, 2017) document how experimentation increases when capital supply increases. This paper contributes to this literature by focusing on the role of financial markets in shaping the strength of startup firms catering incentives and how competition in *VC markets* determines startup's trade-offs between catering and innovating independently.

The literature on the role of exit markets in shaping the direction of innovation among startup firms is limited, but a related area of the literature studies innovation as a determinant of exit outcomes (e.g., Bowen, Frésard and Hoberg, 2019; Bayar and Chemmanur, 2011). Other research has focused on the role of innovation assets in motivating merger and acquisition activity (e.g., Bena and Li, 2014; Hoberg and Phillips, 2010). This paper instead highlights the importance of expectations regarding exit markets in shaping the ex-ante innovation decisions of new firms. Thus, while past innovation activity shapes exit outcomes, the types of innovations that eventually reach the market are determined by entrepreneurs' and investors' expectations regarding financing and exit conditions.

The paper is also related to the literature on the boundaries of the firm, with a focus on innovation activities. Incomplete contracting motivates putting complementary assets under shared control (e.g., Grossman and Hart, 1986; Hart and Moore, 1990). Indirectly, my results relate to alternative forms of financing and contractual agreements such as strategic alliances and corporate VC. Through catering, new firms maximize the acquisition option by incorporating the innovation incentives of the incumbent firms, suggesting that incumbent firms partially outsource their innovation activities. A similar mechanism is documented by Phillips and Zhdanov (2013) who show how the prospects of selling out to a larger firm incentivize smaller firms to innovate more, while larger firms optimally decrease R&D spending in favor of acquiring smaller firms. However, they do not study the direction of innovation or the type of innovations but only the firms' spending on R&D. Further, they only study public firms and not the inherent trade-off between the two exit routes that are important for the type of innovations startup firms produce that are the focus of this paper. Bena, Erel, Wang and Weisbach (2021) study the post-merger changes in the specificity of merging firms' patent output using text-based similarity measures of patents; the measures are distinct but similar to those developed in this paper and more apt for capturing asset specificity.[9]

Lastly and importantly, this paper is related to the literature on the antitrust concerns with regards to acquisitions of small firms. Many innovating firms are acquired early in their lifecycle before they have established a solid presence in the market. Since the early 2000s the number of VC exits by acquisition in the US has soared as shown in fig. 1 (the same trend has been documented by, e.g., Wang, 2018; Bowen et al., 2019). The drawbacks of high acquisition activity, especially acquisitions that fall below the thresholds of pre-merger review, have received attention in academic and policy circles alike (e.g., Wollmann, 2019).[10] Cunningham et al. (2021) provide evidence of acquisition activity driven by anticompetitive motives, where firms are acquired, and projects are killed to avoid cannibalization. I document a different concern arising from increased acquisition incidence of small firms—distortions in the ex-ante incentives to innovate. New firms, both those that are eventually acquired and those that remain independent, have an incentive to introduce less independent innovations. The type of innovations that eventually reach the market on aggregate become more similar to incumbents' assets when firms strategically cater.

3 Theoretical Framework

In this section, I provide a theoretical framework modeling how startups' incentives to innovate in a less independent direction are affected by exit market expectations. The analysis focuses on the startup's decision to adjust their innovation strategy to accommodate catering incentives by redirecting effort toward innovation activities complementary to potential acquirers. By catering, the value of the startup as an acquired entity increases. An increase in the acquisition option benefit the current owners of the startup in three ways: i) in the event of an acquisition, the owners fully enjoy the increase in the value of the startup as an acquired entity; ii) the bargaining position of the firm owners vis-à-vis external investors improve and the current owners expect to retain a larger share of the surplus following future external financing rounds; and iii) if multiple external financing rounds are needed, the firm will benefit from an increase in the expected value

[9]Specifically, Bena et al. (2021) compute the cosine similarity of a weighted vector representation of two patents. They use a term-frequency-inverse-document-frequency (TF-IDF) scheme similar to Kelly, Papanikolaou, Seru and Taddy (2018). More weight is assigned to words that are less common in other patents, reflecting the shared "specificity" of the expression. The TF-IDF weighting depends on what patents are included for comparison (e.g., what time horizon).

[10]The rise of dominant firms, especially in the technology sector, has drawn the attention attention of policy-makers, antitrust authorities and academics to anticompetitive takeover activity of small firms that fly under the radar. For example, the Federal Trade Commission (FTC) launched an investigation into all past acquisitions, including non-reportable acquisitions, by Alphabet (Google), Amazon, Apple, Facebook, and Microsoft, to study the antitrust implications of such deals—see Federal Trade Commission (2021).

of the firm.

3.1 Set-up

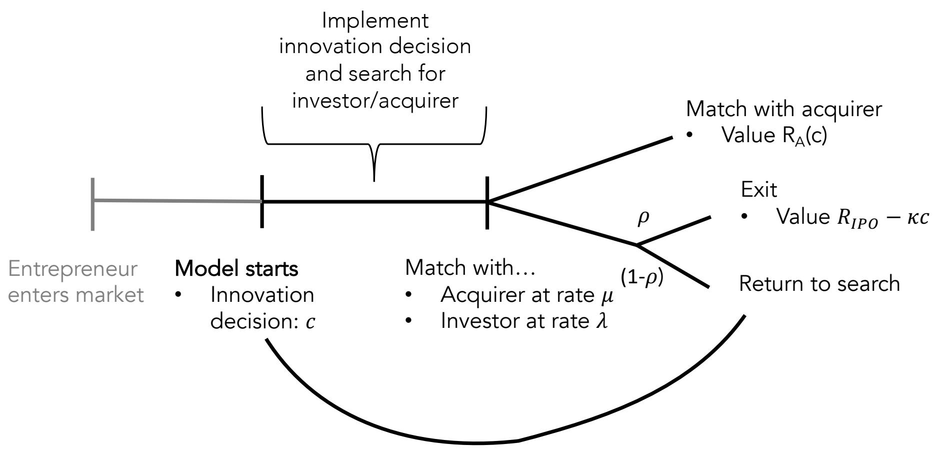
The innovation choice is embedded into a search market framework with two plausible exit markets; an exit through an acquisition or an exit as an independent company (e.g., IPO).[11] The economy is populated by startup firms, investors, and potential acquirers. Time is continuous, and the discount rate is $r > 0$, which is assumed to be common across all investors, including investors searching for investments, and those already invested, and any other current startup owners (e.g., founders). Search frictions are thus represented by the cost of delay. The objective is to model how the firms' incentives to engage in complementary innovation activities are determined by the two exit options and the characteristics of the respective markets.

The startup requires (at least) one additional round of financing, an investment of size I, before the current owners can exit the company in an IPO and receive a payoff R_{IPO}. Alternatively, an acquirer arrives and makes an offer $R_A(c)$. The payoff in the event of an acquisition is an increasing function of the level of complementarity $c \geq 0$. I assume that R_A is concave and increasing in c, such that $\partial R_A/\partial c > 0$ and $\partial^2 R_A/\partial c^2 < 0$. Moreover, I assume that $\lim_{c\to 0} R_A(c) = \underline{R_A}$ such that $0 \leq \underline{R_A} < \frac{r+\mu}{\mu} R_{IPO}$, and that $\lim_{c\to\infty} R_A(c) = \overline{R_A} < \infty$.[12] Both exit directions are plausible for the startup; however, while an acquirer can arrive at any time during the startup's life, an IPO requires at least one more external financing round. The startup's current owners (including the founder and prior investors) are making an innovation decision today, anticipating the two exit routes' relative probability and expected value. An increase in complementary innovations increases the expected payoff in an acquisition but lowers the expected payoff in an IPO. I assume the adjustment costs are linear in the magnitude of the adjustment such that the costs incurred are given by κc. The sequence of events is illustrated in the timeline below. During the search stage, there is always some probability that an acquirer or an investor will arrive. An acquirer arrives with a Poisson arrival rate of μ and makes a take-it-or-leave-it-offer to the current owners of $R_A(c)$. The arrival rate is exogenously determined, and not affected by the startup's owners' decision to adjust their innovation strategy.[13] The deal

[11] My search framework builds on what is commonly known as the Diamond-Mortensen-Pissarides model within the search literature (e.g., Pissarides, 2000).

[12] This is to ensure that an investment is valuable to the owners for some investor arrival rate (λ), otherwise raising external capital would be a negative NPV project even if $\lambda \to 0$. If this condition does not hold, the firm would only engage in complementary innovations.

[13] An alternative specification of the model, where μ is increasing in the level of complementarity instead of R_A, yields very similar results. An increase in c would then increase the expected value of an acquisition, as the



Timeline

arrival rate is akin to a probability measure. A deal will arrive with a probability $\mu \cdot \Delta$ over the next Δ units of time.

The mass of startups currently searching for an investor is given by M_S, and the mass of investors searching for an investment is given by M_V. I define the capital market tightness measure as $\theta = \frac{M_V}{M_S}$, with a higher value of θ representing a market where capital supply is high relative to capital demand. I model the rate at which a startup and an investor match as $m(M_V, M_S)$, where $m(.)$ is assumed homogeneous of degree one, increasing in both arguments, concave and continuously differentiable. For an investor, the Poisson deal arrival rate is given by $M(\theta) \equiv m(M_V, M_S)/M_V = m(1, \frac{1}{\theta})$ where the equivalence follows from the homogeneity of the matching function. The investors' deal arrival rate thus decreases in the capital market tightness measure θ, indicating that the higher the relative supply of capital (M_V) to the demand for capital (M_S), the more difficult it is for an investor to find an investment. Similarly, the Poisson arrival rate from the perspective of the startup is given by $\lambda = \theta M(\theta) \equiv m(M_V, M_S)/M_S = m(\theta, 1)$ which is strictly increasing in the capital market tightness measure (θ). To ensure an interior equilibrium, I assume that:

$$\begin{aligned} \lim_{\theta \to 0} M(\theta) = \lim_{\theta \to \infty} \theta M(\theta) = \infty \\ \lim_{\theta \to \infty} M(\theta) = \lim_{\theta \to 0} \theta M(\theta) = 0 \end{aligned} \tag{1}$$

probability of an acquisition would increase. In the current set-up, the expected value increases in c as the payoff conditional on an acquisition increase.

Conditional on matching with an investor, the firm's current owners ("the insiders") will bargain with the external investors ("the outsiders") over how to split the surplus generated by the investment. I assume a generalized Nash bargaining solution with the insiders' and outsiders' bargaining power given by β and $(1-\beta)$, respectively. The parameter $\beta \in (0,1)$ is exogenously given. After the investment, the firm's owners (including the new investor) find out whether they can exit through an IPO or whether an additional round of financing is required. With a probability ρ, an IPO exit is possible, and with a probability $(1-\rho)$, the startup will need to return to the search market. In practice, the probability ρ is likely to be a function of the startup's life cycle, including its fixed characteristics and time-varying factors internal and external to the firm. For simplicity, I model it as a lottery with an exogenously determined probability distribution. A higher ρ implies the firm is nearer a plausible exit. If the startup finds it will require an additional round of financing, they return to the search stage and will be able to adjust their innovation strategy again.

One feature of the framework is that when the startup receives an investment that results in the startup returning to the search market, the previously external investors now become "insiders" and can enjoy the benefits of the acquisition option. Moreover, I abstract from any contracting issues that might arise from conflicts of interest between the startup's founders, earlier investors, and later investors. For simplicity, I assume that the interests of all current startup owners are aligned—to maximize the expected value of the startup—and that the primary trade-off of interest is given by current owners' interests vis-à-vis future external investors' interests. However, an important feature of the model is that the ability to extract surplus when bargaining depends on whether (VC) capital or good investment opportunities are in relative short supply.[14]

3.2 Equilibrium

3.2.1 Expected Value in Search Stage

The expected value of the current owners' stake in the startup at the start of the model is given by the discounted value of future payoffs ($Ins^O(c)$) as defined in eq. (2a). With a probability

[14] A common assumption in the entrepreneurial finance literature is that capital markets are competitive and the entrepreneur extracts all the surplus. I relax this assumption and allow the (VC) investors' and founders' relative share of the surplus to vary with the capital market tightness measure and study the implications on firms' innovation choice. A similar search market set-up where relative supply affects firm outcomes has been studied by, e.g., Inderst and Müller (2004) and Michelacci and Suarez (2004), and both these papers has inspired the set-up in this paper. The former theoretically study the role of the capital market tightness measure on pricing, contracting, and value creation, while the latter focus on the timing of the exit (through an IPO). Neither considers the implications on innovation strategy or the exit mode.

$\theta M(\theta)\Delta$ an investor arrives over the next Δ units of time, and conditional on matching the expected value of the current owners' stake in the startup after the investment is given by $Ins_I(c)$. Similarly, an acquirer arrives with a probability $\mu\Delta$ and offers $R_A(c)$. By rearranging and taking the limit as $\Delta \to 0$, I obtain the expression for the expected value of the startup in eq. (3a). This is the expected value of the startup of being in the search stage. The expected value is increasing in the arrival rate of an investor θ as well as an acquirer μ, but also in the expected deal values $Ins_I(c)$ and $R_A(c)$.

$$Ins^O(c) = \theta M(\theta)\Delta e^{-r\Delta} \cdot Ins_I(c) + \mu\Delta e^{-r\Delta} \cdot R_A(c) + \big(1 - (\theta M(\theta) + \mu)\Delta\big)e^{-r\Delta} \cdot Ins^O \tag{2a}$$

$$Out^O(c) + I = M(\theta)\Delta e^{-r\Delta} \cdot Out_I(c) + \big(1 - M(\theta))\Delta\big)e^{-r\Delta} \cdot \big(Out^O(c) + I\big) \tag{2b}$$

$$Ins^O(c) = \frac{\theta M(\theta) \cdot Ins_I(c) + \mu \cdot R_A(c)}{r + \theta M(\theta) + \mu} \tag{3a}$$

$$Out^O(c) + I = \frac{M(\theta) \cdot Out_I(c)}{r + M(\theta)} \tag{3b}$$

Similarly, the investors' value of being in the search stage, conditional on expecting to invest I, is given in eq. (3b) where $Out_I(c)$ is the expected value of the new investor's stake in the company post-investment. The searching investors' value of a free unit of capital is clearly increasing in the expected deal utility $Out_I(c)$ but decreasing in the capital market tightness measure as $M(\theta)$ is decreasing in θ.

3.2.2 Bargaining

The respective expected values conditional on an investment, the deal values, are determined by the bargaining outcome, specifically the solution to the Nash problem given in eq. (4). If the bargaining breaks down, the investors and current owners realize their outside options.[15] The current owners (the insiders) retain a share $(1-\alpha)$, and the outsiders obtain a share α.[16] At the time of the bargaining, the investors take the outside options as given. The surplus generated by the investment is given by the expected value conditional on the investment net of the respective value of continuing the search. The respective expected deal values can be expressed in terms of

[15] If bargaining breaks down, the expected deal values are zero in equilibrium. The current owners' outside option is given by the expected value of being acquired, while the investors' outside option is zero in equilibrium.

[16] In this paper I never present a formal solution for α, this requires some additional algebra but does not add anything to the analysis.

the generated surplus as in eq. (5). Each party's deal value increases in their own outside option (the value in search) but decreases in the other party's outside option.

$$\max_{\alpha}\big(Out_I - (Out^O + I)\big)^{(1-\beta)}\big(Ins_I - Ins^O\big)^{\beta} \quad \text{s.t. } \alpha \in (0,1) \tag{4}$$

$$Ins_I(c) = \beta S(c) + Ins^O(c) \tag{5a}$$

$$Out_I(c) = (1-\beta)S(c) + Out^O(c) + I \tag{5b}$$

$$S(c) = \rho(R_{IPO} - \kappa c - Ins^O(c)) - (Out^O(c) + I) \tag{5c}$$

3.2.3 The Innovation Decision

When the startup is in the search state, the owners have the opportunity to adjust their innovation strategy. The current owners of the startup firm choose the level of complementary innovation that maximizes the firm's expected value in the search stage (Ins^O). I assume that the startup is small relative to the total mass of searching startups M_S and therefore does not consider their impact on the equilibrium. Specifically, the firm does not consider the implications their innovation decisions have on the equilibrium value of the investors' outside option Out^O.[17] This is highlighted in eq. (6) by removing the dependence on c in Out^O.

$$\max_{c>0} Ins^O = \max_{c>0} \frac{\theta M(\theta)\beta\big[\rho(R_{IPO} - \kappa c) - (Out^O + I)\big]}{r + \beta\rho\theta M(\theta) + \mu} + \frac{\mu R_A(c)}{r + \beta\rho\theta M(\theta) + \mu} \tag{6}$$

The expression in eq. (6) is obtained by substituting eq. (5a) and eq. (5c) into eq. (3a) and solving for the expected value of the startup. The current owners benefit from a higher level of complementarity c in three ways. If an acquirer arrives with a deal, the owners enjoy the full benefit of the higher acquisition offer $R_A(c)$ but do not have to bear the costs. Related but somewhat different, the owners also enjoy (part of) the benefit from the increase in the expected value of the startup firm conditional on an investment and returning to the search market. Lastly, when matching with an investor, the owners increase the value of their outside option and thus retain a larger share of the generated surplus but do not have to bear the full costs incurred in

[17] This assumption can also be motivated by allowing for free entry of investors. In equilibrium, the value of a free unit of capital will be determined by the entry costs, and $Out^O + I$ will equal the entry costs.

the event of an IPO.

$$\frac{\partial R_A(c^*)}{\partial c} = \kappa\beta\rho\frac{\theta M(\theta)}{\mu} \tag{7}$$

The optimal level of complementary innovation (c^*) satisfies the first-order condition in eq. (7). The left-hand side decreases in the level of complementarity, while the right-hand side is determined by exogenously given variables and is strictly positive. If the right-hand side is too large, e.g., if the costs κ are too high, the capital market tightness measure is very large, or the arrival rate of an acquirer is low, then the optimal level of complementarity goes to zero or is equal to zero.[18] However, if the right-hand side is very small, then the optimal level of complementarity goes to infinity. Under the assumption that all parameters are well-defined, the program in eq. (6) has a unique solution.

Proposition 1 (Optimal level of complementarity)**.** *The optimal level of complementarity c^* satisfies*

$$\frac{\partial R_A(c^*)}{\partial c} = \begin{cases} \kappa\beta\rho\frac{\theta M(\theta)}{\mu} & \textit{if } \kappa\beta\rho\frac{\theta M(\theta)}{\mu} < \frac{\partial R_A(0)}{\partial c} \\ \frac{\partial R_A(0)}{\partial c} & \textit{otherwise} \end{cases}$$

This implies that complementarity increases in the arrival rate of an acquirer μ and decreases in the capital market tightness measure, as well as in the probability of an IPO conditional on receiving an investment ρ, the bargaining power of the entrepreneur β and the costs incurred in the event of an exit by IPO. As such:

- *An increase in relative capital supply will decrease the startups' incentives to engage in complementary innovation activities;*
- *If the expected time to exit in an IPO is long, the startup's optimal innovation strategy is more sensitive to changes in the relative expected value of the two exit modes; and*
- *If the probability of an acquisition is very low, the startup is unlikely to engage in complementary innovation activities but is more sensitive to changes in relative capital supply.*

Proposition 1 states that the marginal benefit from complementarity must equal the marginal cost of complementarity. This trade-off depends on model fundamentals such as the expected

[18] I have not made any assumptions concerning $\frac{\partial R_A(0)}{\partial c}$, except that it is positive. It is possible that $\frac{\partial R_A(0)}{\partial c} < \kappa\beta\rho\frac{\theta M(\theta)}{\mu}$, in which case $c^* = 0$ as c cannot be negative (by assumption).

time to exit in an IPO, the probability of finding an acquirer, and the costs of complementary innovations. More importantly, however, the relative importance of such factors depends on the availability of capital, specifically the competition in the VC market.

3.2.4 Equilibrium

I consider a stationary equilibrium, in line with the search market literature. This requires that the inflows of new entrepreneurs and investors equal the outflows. If m_S and m_V are the inflows of new startups and investors, respectively, then the conditions in eq. (8) must hold in equilibrium.

$$\begin{aligned} \dot{M}_S &= m_S - M_S(\mu + \rho\theta M(\theta)) = 0 \\ \dot{M}_V &= m_V - M_V M(\theta) = 0 \end{aligned} \tag{8}$$

I obtain the equilibrium level of capital market tightness by solving for the masses M_V and M_S in eq. (8), dividing the expressions with each other and solving for $\theta M(\theta)$ (eq. (9)). This has a unique solution as long as $m_S > \rho m_V$. The stationarity condition determines the equilibrium capital market tightness measure for exogenously given inflows, given that there is a unique mapping from θ to $\theta M(\theta)$.

$$\theta M(\theta) = \mu \frac{m_V}{m_S - \rho m_V} \tag{9}$$

Definition 1 (Equilibrium)**.** *In equilibrium the following conditions must hold:*

- *The bargaining outcome (α) solves the program in eq.* (4)*;*
- *The expected value of the startup and VC capital in the search stage satisfy eq.* (3)*;*
- *The startups' owners choose the complementary innovation level c to maximize eq.* (6)*; and*
- *The inflows and outflows satisfy the stationarity condition in eq.* (8)*.*

I obtained the second expression in eq. (6) by combining the solution to the bargaining problem (eq. (5)) and the expected value equations in eq. (3). The solution to this problem is given in eq. (7). By substituting the summarized stationarity condition eq. (9) into the optimal innovation choice condition, I obtain the equilibrium condition in proposition 2.

Proposition 2 (Equilibrium)**.** *Given the inflows m_S and m_V such that $m_S > \rho m_V$, an equilib-*

rium exists and is unique. The equilibrium is fully characterized by:

$$\frac{\partial R_A(c^*)}{\partial c} = \begin{cases} \kappa\beta\rho\frac{m_V}{m_S-\rho m_V} & if \quad \kappa\beta\rho\frac{m_V}{m_S-\rho m_V} < \frac{\partial R_A(0)}{\partial c} \\ \frac{\partial R_A(0)}{\partial c} & otherwise \end{cases}$$

The equilibrium condition implies that:

- *The optimal level of complementarity is non-negative but can be zero when the costs are too high, or the inflow of new capital is high; and that*
- *The optimal level of complementarity is* always *(weakly) decreasing in the inflow of new capital for all reasonable levels of m_V relative to m_S.*

The optimal innovation choice in equilibrium is a function of the relative inflows of new entrepreneurs and new investors, in this model assumed to be exogenously given. An exogenous increase to the inflow of capital results in a decrease in the startup firms' catering incentives in equilibrium as shown in proposition 2. This prediction corresponds to the hypothesis that I empirically test in section 7.

4 Description of Data and Innovation Measures

The objective is to understand how financial market characteristics, including acquisition market attributes and capital market competition, affect the direction of innovation among new firms. I use Venturexpert as well as trademark and patent data from the USPTO to compute the innovation measures.

4.1 Startup Firms

From Venturexpert, I obtain a sample of US firms that were founded in 1980 or later. The full sample consists of 33,435 VC-financed startups (see table 1). A significant number of firms in the Venturexpert database are missing the founding date variable, and I use CapitalIQ to fill in the missing values by matching on name and state and approximate financing rounds. I only include firms that at some point after 1980 received VC financing and where the date of first investment is not missing and occurs after the date of founding.

The sample of firms is limited to firms that have received VC-financing at some point in time. First, VC-financed firms are a suitable setting as it enables the identification strategy outlined in section 7. Moreover, while VC-financed firms only constitute a small fraction of all new firms in the economy, they also comprise a significant fraction of high-growth firms that contribute disproportionately to economic growth. However, not all business projects are suitable for VC financing, and many high-growth young firms receive alternative sources of capital. It is therefore important to bear in mind this selection effect when interpreting the results. The use of VC-financed firms is also partially motivated by data availability reasons. The sample is likely a representative sample of VC-financed startups, including also those startups that eventually fail.

From Venturexpert, I also obtain information on which industry the firm operates in and observe the first and subsequent rounds of financing and the current situation of the firm. I thus know if the firm has gone public, been acquired or failed, or gone through some other exit event. A firm exits the sample when they go through an exit event.[19] From Venturexpert, I also acquire information on the timing of financing rounds, the financing stage, as well as round amount and valuation. However, round amount and other round-related information are missing in most parts of the sample. Lastly, from Venturexpert, I also obtain VC fund data, including the closing date of each fund, investment type and focus, fund size and sequence number, firm, and some information on their investments.

The distribution of founding year and year of first investment is presented in fig. 2. The full sample of firms includes all firms that match the above criteria. The other samples include only the firms that I have matched to a trademark or a patent. In comparison (unreported) to all venture-financed firms in the CapitalIQ database, it appears that the Venturexpert database has good coverage in the period 1980-2010; however, newly founded firms increased substantially in the CapitalIQ database after 2010 but remain relatively stable in the Venturexpert database, indicating some incompleteness in the later part of my sample.

4.2 Innovation Data Sources

Previous research on innovation has primarily relied on patent data. In this paper, I extend the scope of innovative activity studied by complementing patent data with information from trademarks. While patents describe technological innovations well, they do not capture other innovation activity that we commonly associate with innovative startups, including novel business

[19]For a large number of firms, the status variable in Venturexpert is "active", and in particular those firms founded in the latter part of the sample remain unresolved. I drop the firm from the sample when more than seven years have passed since the last round or deal (including all types of rounds and deals, not just VC financing).

models, process innovations, and product enhancements. Moreover, some industries are relatively overrepresented among industries with high patenting activity. By studying the trademark data, I have a more representative sample of the underlying industry distribution of the complete sample of VC-financed firms. I use the information in the trademark and patent dataset to construct two distinct sets of innovation measures.

I use the USPTO Trademark case file dataset to construct the first set of innovation measures. The trademark dataset has near full coverage of all trademark applications and publications after 1982 and includes general information such as application and publication date, ownership assignment, and a statement. The applicant must outline for which goods and services (products) protection is sought in the statement section. Trademark protection only extends to those goods and services listed in this section. The text is somewhat standardized, and "The language used [...] should be understandable to the average person".[20] The text is not very descriptive; in particular, it does not describe what makes the firm's products unique. I use the data to measure the scope of a firm's product offering, including both goods and services, rather than their level of differentiation within a specific product market category.

Moreover, the applicant must also provide proof of use in commerce before the trademark is published. The dataset covers the date of first use and date of first commercial use of the listed goods and services. These dates better reflect the true introduction patterns by the firm than application or publication dates. From the case file dataset, I can follow the evolution of the goods and services the firm offers to its customers and from which point in time these goods and services are commercialized. The scope of the goods and services section can be amended over time, and firms can also file a trademark on the basis of intent to use. For the trademark to eventually grant protection, the firm must provide proof of use.

The second set of innovation measures are constructed using patent data. I use patent data from the USPTO Bulk Data Storage (BDS). The BDS dataset has near complete coverage of all patent grants from 1976 through today and most patent applications from 2001 and onwards. I only use granted patents, as the coverage and information are better over the sample period. The data includes general patent and application information, such as application date, grant date, and assignees (owners), including reassignments and citations. Most importantly, it contains the full text from the claims section of granted patents. The claim(s) of a patent "shall define the

[20] US Patent and Trademark Office (2020).

matter for which protection is sought".[21]

The claim section describes the new technology and should fully characterize the scope of the innovation and its distinguishing features. The claim determines the scope of the patent holder's rights and is also where the applicant defines what makes the innovation unique. For the patent to be granted, the innovation must be distinguishable from previous patents.

I link the patents and trademarks to the startup firms using the respective assignment datasets. I match based on name (standardized using reclink2, see, Wasi and Flaaen 2015) and state to the patent assignee data and trademark ownership files. Moreover, I also require that the firm was founded before the assignment of the trademark or patent to the firm. This procedure may underestimate the true innovation activity of firms (false negatives), but it is unlikely it overestimates innovation activity by introducing a lot of false matches. Some comparisons of the sample of trademark and patent firms are presented in table 1. About 55% of the firms in the sample has applied for trademark protection and 22% for patents. A smaller fraction has introductions that span more than one year (about 33% and 16%). I use the date of first use as this more accurately reflects the actual introduction pattern. However, an additional benefit is that more startups can be included in the analysis, as the empirical strategy requires at least two startup-year observations.

Firms with patents are very likely also to have trademarks, but the reverse does not hold. I can therefore study the direction of innovation of a much more significant fraction of the startup economy by exploiting the information in the trademarks. Compared to the underlying sample, patenting firms have a relatively higher representation in the biotechnology, medical/health, and semiconductor/electrical components industry as shown in fig. 3. In contrast, the industry distribution of firms with trademarks aligns well with the full sample of VC-financed firms. Moreover, sample firms with patents and trademarks are more likely to have had a successful exit (IPO or acquisition). Part of this might reflect that older firms have had more time to file for patents and trademarks and exit. However, the failure rate is also lower among this subset of firms.

Patent and trademark firms also raise more financing rounds than the average VC-financed firm. The timing of the introduction of new patents and trademarks across the different samples is presented in table 2. In general, it appears that patenting activity precedes trademarking activity, as firms are on average younger at the time of the first patent application when comparing the

[21] PCT article 6, `https://www.uspto.gov/web/offices/pac/mpep/s1824.html`.

trademark sample to the patent sample and within the sample of firms with both patents and trademarks. Patenting firms also appear to go through more financing rounds than firms with trademarks. Lastly, the sample's number of new patents and trademarks is highly skewed, with the mean significantly larger than the median. However, this pattern is not as prevalent for the number of patent-year or trademark-year observations.

5 The Direction of Innovation

The objective is to study the effect of a changing exit market structure on firms' innovation strategy and financial markets' role in shaping the startup owners' incentives to adjust their innovation strategy. First, I hypothesize that high acquisition market activity is associated with more innovation in the direction where acquisition markets are more attractive, suggesting that firms strategically adjust their innovation strategy and invest in more complementary innovation. Increasing complementary innovation should increase the probability of finding an acquirer and the value in an acquisition. Second, I study the role of the availability of capital. When capital is scarce, firms invest more in complementary innovations. There are two reasons for this strategic adjustment in response to capital scarcity. First, if firms cannot raise capital, they have an alternative exit strategy. Second, if the startup owners find an external investor, they can leverage their outside option to negotiate better terms.

The first challenge in addressing this question empirically is measuring the direction of innovation of startup firms. First, I cannot observe a firm's innovation strategy, only its innovation output. Second, I need to measure the direction of their innovation strategy, specifically which areas they are innovating within and how that direction changes with acquisition activity. To assess the direction of innovation of the startup firms, I use a sample of potential acquirers and compute the similarity of the startup firm's innovation output to the potential acquirer's innovation for each possible startup-acquirer year observation. The measure of acquisition activity is then constructed based on recent acquisitions of other startup firms similar to the acquirer. It is akin to a network structure, where potential acquirers and startups are nodes. The complementarity measures assess the strength of the ties between each startup and each potential acquirer. I then test whether firms gravitate closer toward firms where acquisition activity is high. I do not measure the ties between potential acquirers nor between different startup firms.

5.1 Similarity

I use the Compustat universe of US firms as the sample of potential acquirers covering all listed US firms and include the public firms a couple of years prior to their IPO. As some firms in the startup sample eventually enter the Compustat sample, I ensure that there is no overlap. I match the Compustat firms to the USPTO datasets the same way as patents and trademarks were matched to the firms in the Venturexpert dataset. The true sample of potential acquirers most likely extends beyond this sample and includes other private and foreign firms. I cannot include non-US firms in the sample as the scope of their innovative assets is less likely to be fully represented by the USPTO datasets, and private firm data are scarce. However, I am interested in how acquisition activity in an area affects the direction of innovation, not in the actual acquisition event. One potential acquirer represents a direction of innovation, not necessarily the actual future acquirer. Moreover, I study all startup firms before their exit outcome is known, and the sample includes firms that eventually are acquired and firms that exit via an IPO or fail.

For each firm-year, for both startup and potential acquirer firms, I construct a panel with the portfolio of trademarks and patents they hold (respectively). A patent is included in the portfolio until it expires, approximately 20 years after the filing date, and trademarks are included in the portfolio if they are “live”. I also construct panels of new patents or trademarks; I refer to these as new introductions. The two set of panels are distinct in the sense that the panel of portfolios represents the *stock* of innovation assets while the new introductions are *inflows*. When referring to trademarks, I use the date of first commercial use of the described good or service rather than the date of application/publishing date. The date(s) can thus span several years, as products and services could be introduced commercially at different dates but be included in the same trademark. For patents, I use the application date as the date of introduction.

I compute the pairwise (normalized) cosine similarity score to measure the similarity between the different firms' innovation assets. Cosine similarity is the cosine of the angle between two N-dimensional vectors and a commonly used measure of similarity between two text corpora. Hoberg and Phillips (2010) use cosine similarity measures to study the role of product market synergies in acquisitions as well as in a series of subsequent papers. For example, a similar approach underlies the new industry assignments developed to study the competitive environment in various product markets in Hoberg and Phillips (2016).

The text corpus is translated into a vector representation where each word represents one element, a word indicator vector. I remove all stop words using the "stop_word" lexicon (pooled from three separate stop word lexicons) from the Tidytext package (Silge and Robinson, 2016) and transform the word count vectors into word indicator vectors ($I_{i,t}$). The element n of firm i's vector is 1 if the word is used in the patent claim text or trademark statements, and 0 otherwise. When comparing two portfolios, I thus ignore the information that one portfolio uses the word "algorithm" X times to describe Y different products, while the other portfolio only uses the word Z times. I transform the word vectors at the level of the unit of observation, at the portfolio (stock) level, or the level of each new introduction (flow).

When using indicator vectors, the cosine similarity measure can be rewritten as a function of word counts, see eq. (10), greatly reducing the computational efforts. A more comprehensive account of the computation of the similarity measures is available in appendix A1.

$$S_{ij,t} = \frac{I_{i,t} \cdot I_{j,t}}{\|I_{i,t}\|\|I_{j,t}\|} = \frac{\text{Common words}_{ij,t}}{\sqrt{\text{Distinct words}_{i,t} \cdot \text{Distinct words}_{j,t}}} \tag{10}$$

For each year, I compute the pairwise similarity measure for each potential acquirer firm's portfolio to each startup's portfolio using both the patent and trademark portfolios, comparing stock to stock. I also compute the pairwise similarity in each year between the potential acquirer's portfolio and the startup firm's new patents and trademarks in the given year. In the latter, I compare the inflow for startups to the stock of the potential acquirer. For each startup firm-year, I obtain a (large) set of pairwise similarity scores with every firm in the US public market universe, comparing *portfolio to portfolio* or *new introductions to portfolio*. New introductions encompass new patents or new additions to the trademark's goods and services description(s) in a given year. I can aggregate these pairwise observations to get firm-year level observations or use the relevant pairwise observations. Only a subset of pairwise observations is "relevant"; most companies have zero or minimal overlap in their innovation activities. For this reason, I mainly restrict the attention to the ten closest potential acquirers.

5.2 Direction

For each startup year, I have the pairwise similarity score with respect to all firms in the Compustat universe, comparing either portfolio-to-portfolio or new introduction-to-portfolio. A change in this measure could be driven by the potential acquirer's decision to enter the same product space as the startup firm entered five years ago or by their decision to sell some of their assets, rather than changes in the startup firm's innovation strategy. I restrict attention to startup years with new introductions, construct a dataset with a startup introduction year as the observational unit, and only consider the potential acquirers with the top ten highest scores *before* the introduction.[22] For each startup-year, I have up to ten observations with potential acquirers' that are reasonably close.

These form the baseline portfolios, and I study the changes in a firm's portfolio composition at the time of new introductions. Specifically, I look at three measures: $Score_{iat}^{Introduction}$, $Score_{iat}^{Portfolio}$, and $I(StaysTop10)_{iat}$. $Score_{iat}^{Introduction}$ is the similarity measure between the firm's new introductions (inflow) and the portfolio (stock) of the previous close potential acquirer. It compares the similarity of a firm's new introduction to the portfolio of the potential acquirer just before the new introduction, specifically at the beginning of the year of.[23] This measure compares the similarity of the firm's recent innovation efforts to the current portfolio of the potential acquirer. The second measure, $Score_{iat}^{Portfolio}$, is similar to $Score_{iat}^{Introduction}$ but compares the startup firm's portfolio, after the new introduction, to the portfolio of the potential acquirer, e.g., it compares the startup's post introduction stock to the potential acquirers' stock. The portfolios represent the cumulative efforts since each firm's inception, measured when the startup firm has made an active change to its portfolio. It more accurately reflects the positioning or scope of the firm within the area. The last variable, $I(Staysintop10)_{iat}$, is an indicator variable that takes the value one if the potential acquirer remains among the top ten closest after the new introduction.

Sample summary statistics for the trademark and patent innovation measures used in the empirical analysis are displayed in Panel A and B of table 3. The scores are relatively symmetrically distributed within the bounds $(0, 100)$. Some trademark scores have perfect similarity (a score of 100), while such high scores never occur in the patent sample. Trademark goods and services text are on average shorter and more standardized. While the format of the patent claims section follows a specific structure, the "writer" has much more discretion in the length and detail of the text.

In appendix A2, I show how the distribution of the two scores $Score_{iat}^{Portfolio}$ and $Score_{iat}^{Introduction}$ evolve as the startup firms age and relative to their first VC investment. The median and av-

[22] Alternative criteria such as the top five closest or a similarity score above a certain threshold yield similar results.

[23] I can also use alternative specifications by, e.g., lagging the portfolio by some years or using the data after the previous introduction.

erage within the cross-section coincide well, suggesting the scores are relatively symmetrically distributed in the cross-section when controlling for life-cycle characteristics. However, the portfolio score appears to increase over time, in particular the patent-based scores. The trend is, if anything, negative for the new introductions ($Score_{iat}^{Introduction}$) but not as prominent in comparison to the portfolio-based scores. In fig. A.2.3 and fig. A.2.4, the distribution of introduction level scores is plotted against years relative to first investment and exit for the subsample of firms with a coded exit. There are no clear patterns across these groups of firms.

6 Choice of Direction

In this section, I study the direction of innovation. First, I outline the empirical specification in section 6.1 and discuss its benefits and limitations. The results are discussed in section 6.2.

6.1 Empirical Strategy

The baseline specification is the model in eq. (11) with $I(StaysTop10)_{iat}$, $Score_{iat}^{Introduction}$, and $Score_{iat}^{Portfolio}$ as the outcome variables. As described in section 5.2, $I(StaysTop10)_{iat}$ is an indicator variable taking the value one if potential acquirer a remains among startup i's top ten closest potential acquirers after the introduction of a new patent or trademark by the startup and zero otherwise. I interpret this as firm i deciding to innovate in the direction of acquirer's area a. The other two variables instead measure the magnitude of similarity, with $Score_{iat}^{Introduction}$ measuring the intensity with which a firm is innovating in a given direction, comparing the startup's new additions (flow) to the existing assets of potential acquirers (stock). $Score_{iat}^{Portfolio}$ is less informative about recent changes in the firm's own innovation strategy but does indicate whether the firm's recent innovation activities are significant enough to drive larger changes in innovation complementarities as the measure compares the post-introduction portfolios (stock) of the startup and potential acquirer.

$$Y_{iat} = \beta_1 AA_{at} + \beta_2 X_{it} + F.E. + \varepsilon_{iat} \tag{11}$$

Acquisition activity AA_{at} is measured at the acquirer year level and constructed from the exits of firms in the startup sample. Figure 4 illustrates the construction of the acquisition activity score. I count the number of startup firms that i) had potential acquirer a among their top ten closest based on the portfolio score at the beginning of the year and ii) exit the sample by being acquired in the given year. I then take the lagged three-year average of this measure to construct AA_{at}. Note that a firm exits the sample once it is acquired (or when it goes through some other exit event), and as such, the startup firms used to construct AA_{at} are not in the sample in year t. I do not measure the similarity to the acquired firms or the actual acquirer, but instead, let the Compustat firm represent an "area" or a node in the network.

An alternative would be to compare the startup firms' trademarks and patents directly with the acquired startups or with the acquiring firm's innovations. I would then lose variation at the level of the potential acquirer (representing a possible direction of innovation), and it is not clear ex-ante whether the acquisition of a similar startup firm would suggest the given direction is more or less attractive.[24] As the objective is to obtain consistent estimates of how startup firms adjust their innovation strategy to differences in the relative attractiveness of the acquisition market, the measure of acquisition activity used is more appropriate, as it measures the general activity in an area.

The summary statistics of AA_{at} are presented in panel C and D of table 3. There are many potential acquirer areas where past acquisition activity was non-existent. Of the observations, 24% and 14% are equal to zero for the trademark and patent sample, respectively. The median score is 1 and 1.33, respectively. However, I am primarily interested in the variation within each startup year observation, and there is significant variation within the groups. This is evidenced by the second row of each panel (Max-Min) where I compute the difference between the highest and lowest AA_{at} in the startup-year group and compute the summary statistics for this variable.

X_{it} is a vector of startup level controls that vary between rounds and includes the number of capital rounds the firm has raised as well as changes in capital inflows to the local VC market in the firms' industry. The set of controls are highly limited by the availability of startup-level data and by no means control for all unobserved heterogeneity that might affect the estimator. To address this concern, I include a set of fixed effects in the model in eq. (11). The fixed effects account for potential unobserved heterogeneity that the limited set of control variables cannot. In all specifications, I include startup and year fixed effects or startup-year fixed effects.

[24] Kamepalli, Rajan and Zingales (2020) study the "Kill zone" in the digital platform industry. They propose a theoretical model where major acquisitions can deter entry and innovative activity in industries with significant network externalities. They document a decrease in VC investments in new firms following acquisitions by large incumbents. On the other hand, Phillips and Zhdanov (2017) document a positive association between M&A activity and VC investments.

It is important to understand the structure of the data to understand the role of the fixed effects. While each observation is measured at the startup-acquirer pair level, the observational unit in the data is a startup firm introduction. A new startup-acquirer pair replaces a startup-acquirer pair if the startup innovates in a different direction. Thus, I can control for any time-invariant unobserved factors that affect all i-firm pair observations by including startup fixed effects. This is important for the specification, as firms are likely to differ in their average level of similarity with respect to potential acquirers. The average score of startups of a particular type might be higher, but I am interested in changes in their innovation strategy, specifically with respect to the direction—do they innovate more in directions where acquisition activity is relatively higher? The inclusion of year fixed effects controls for any unobserved time heterogeneity that affects all firms similarly.

I also estimate eq. (11) and include startup-year fixed effect, controlling for time-varying unobserved factors at the startup level. This would subsume all time-varying controls but allow for identification of β_1 based on only the variation within the group of the top ten closest firms of firm i at time t. A positive β_1 implies that firms innovate more in the direction of more acquisition activity. It is important to note that I can only assess whether the direction of a firm's innovation strategy correlates with acquisition activity, and I make no causal claims.

Potential acquirer fixed effects can not be included in the specification. The strategy is constructed to understand how the firms choose the direction of innovation, the magnitude of such efforts in an area, and the implications on the firm scope. The inclusion of acquirer fixed effects implies estimation within an area defined by the innovation effort and acquisition choices of firm a and effectively removes cross-group comparisons. These cross-group comparisons are important for the firm's innovation decision, including such fixed effects would remove the desired variation.

One concern with the specification is that the measure of acquisition activity (AA_{at}) correlates with demand for the underlying asset. This is highly likely, and an increase in demand for the underlying assets is also most likely a key driver of acquisition activity. Currently, within the bounds of this specification, I cannot separate high acquisition activity from general demand. For now, I let it suffice with the interpretation that firms are more likely to innovate in the direction of areas where acquisition activity is high. In section 7, I exploit a natural experiment and provide evidence that firms introduce less complementary innovations following a plausibly exogenous decrease in the relative attractiveness of an acquisition. I exploit a policy change that increased relative capital supply. If it was purely demand driving the increase in the similarity measures, then innovation activity within an area with high acquisition activity should increase following a relaxation of financing constraints.

Lastly, I estimate all models using the sample of trademark and patenting firms separately. While there is some overlap between these samples, the similarity measures are distinct. The trademark sample contains more unique startup firms (larger cross-section) while patenting firms have more new introductions (more observation in the time series).

6.2 Results

The results from estimating eq. (11) with $I(StaysTop10)_{iat}$ as the outcome variable are reported in table 4. This is a linear probability model estimating the probability that a startup firm i chooses to innovate in the direction of the previous close potential acquirer a in an area where acquisition activity is high. A positive estimate of β_1 suggests that firms are more likely to stay similar to the acquirer if acquisition activity in the area a is high.

The results in table 4 indicate that firms are relatively more likely to innovate in the direction of a if this direction is associated with more acquisition activity. For a one-unit increase (corresponding to one more acquisition on average in the past three years) in acquisition activity in potential acquirer area a, the probability that a firm chooses to innovate in that direction increases by 0.4–0.5% in the product (trademark) sample and 1.6–1.8% in the patent sample. Thus, for a one standard deviation increase in the acquisition activity measure, this corresponds to about a 2% and a 5% increase in the probability that startup firms remain close to a given potential acquirer for the trademark and patent sample respectively.[25] These results are stable across the different specifications, namely the inclusion of time-varying control variables or changing from startup and year fixed effects to startup-year fixed effects, and statistically significant.

A little more than half of the top ten closest potential firms exit the trademark sample, the average of $I(StaysTop10)_{iat}$ is 49% (table 3), and the share of firms staying in the sample is very diverse across startup-year observations, as shown in fig. 5. For patenting firms the turnover is lower, with average $I(StaysTop10)_{iat}$ is equal to 61%. It is important to bear in mind that even if firm a exits startup i's portfolio of closest firms, the similarity between startup i and a will still be larger than zero, and the similarity between a and the other potential acquirers in the

[25] The in sample standard deviation for the acquisition activity measure is 4.39 and 2.81 for the trademark and patent sample, respectively (Panel C and D in table 3).

portfolio is most likely larger than zero as well. The distinction between a firm among the top ten closest and a firm just outside is somewhat unclear, and the cut-off at ten is arbitrarily chosen.[26] What the results suggest, however, is that startup i is more likely to choose to innovate in a direction with more acquisition activity. However, the structure of the sample limits the firm's direction choices to related areas, not reinventions of the firm's business. A firm producing and selling sugar-free ice cream does not have automated cars in their choice set but would probably have other forms of foodstuff in their choice set, or products that complement the production and sale of sugar-free ice cream.

Exits from the group of top ten closest are driven by changes in the direction of startup firm i's innovations or the new introduction by the potential acquirer or other acquirers in the sample. While it is important to bear this in mind, this also introduces important variations. Assume that potential acquirers a_1 and a_2 were very close to each other as well as to firm i at time t. After this, the two acquirers innovated in different directions. The results suggest that firm i is more likely to innovate in a similar direction as a_1 if acquisition activity in a_1's area is higher than in acquirer a_2's area.

The results in table 4 show that firms are more likely to innovate in areas where acquisition activity is high. First, if acquisition activity is higher in a given area, firms should dedicate more effort into complementary innovation in that area, corresponding to a positive β_1. Having a high level of complementarity should increase both the probability of finding the acquirer and the firm's value in the event of an acquisition. Thus, firms should dedicate more innovation effort into areas where acquisition activity is high if they want to maximize the expected value of the acquired firm.

$Score_{iat}^{Introduction}$ measures the similarity between startup firm i's new introduction and the portfolio of acquirer a at the beginning of the year. This directly measures the magnitude of similarity between a firm's new introduction and the area of acquirer a. The results from estimating different variants of eq. (11) with $Score_{iat}^{Introduction}$ as the outcome variable are reported in columns 1-4 in table 5. The results suggest that the magnitude of firms' complementary innovation activities is higher in areas where acquisition activity is high. The average score in the trademark sample is 21.08 and 18.35 in the patent sample (table 3), suggesting that the similarity score of firms increase by about $0.5 - 1\%$ if average past acquisitions increase by one unit and that the

[26] The results are similar when using other cut-offs such as the top five closest, or all potential acquirers in the top percentile(s).

magnitude of complementary innovation increases with acquisition activity. This corresponds to a $2-4\%$ increase in $Score_{iat}^{Introduction}$ for a one standard deviation increase in the acquisition activity measure.

The results using the portfolio-to-portfolio score ($Score_{iat}^{Portfolio}$) after the new introduction are presented in column 5-8 in table 5. We should expect the coefficient estimates to be smaller in magnitude, as portfolios summarize the cumulative efforts of the startup firm's innovation efforts since its inception. The new introduction scores measure the direct relevance of a new introduction relative to the portfolio of a potential acquirer, while the portfolio scores measure the relative scope of a firm's portfolio, comparing the two firms' stocks of innovations right after a new introduction by the startup firm. New introductions in a given area do not mechanically increase the scope for two reasons. First, startup i's new introduction can have a very high overlap with their own portfolio prior to the introduction. Second, it is plausible that new introductions are introduced to level the relative scope across areas rather than to expand the scope in areas with high acquisition activity. The positive and significant coefficient estimate β_1 on acquisition activity suggests that firms increase their scope in areas where acquisition activity is high. From table 3, the average portfolio score after new introductions in the trademark and patent sample are 28.46 and 31.31, respectively. The coefficient estimates in table 5 suggest that for a one-unit increase in past acquisition activity, the scope of the firm in that area are on average 0.2% higher after a new introduction or $0.5-1\%$ for a one standard deviation increase in the acquisition activity measure.

7 Changes in Incentives

In this section, I develop and test whether firms adjust their innovation strategy to changing incentives and introduce more complementary and less independent innovations when an acquisition becomes relatively more attractive, or vice versa, by testing the mechanism outlined in section 3. The intention of the specification in eq. (11) is to understand the direction, scope, and magnitude of a startup firm's innovation efforts in relation to acquisition activity. The empirical specification in this section directly addresses the question: Do firms introduce more (less) complementary innovations when a future acquisition becomes relatively more (less) attractive?

To address this question, I build on the theoretical framework outlined in section 3. Specifically, an increase in relative capital market supply increases the relative value of staying independent, assuming that the firm requires additional financing rounds from external investors. Within the framework, the current owners of a firm can benefit from increased complementarity in three ways. First, in the event of an acquisition, the owners' payoff increases in the expected synergies. Second, the acquisition option remains after a firm raises external capital, and a higher payoff in the event of a future acquisition also benefits the owners if a future exit as an independent firm is unlikely. Lastly, the owners benefit from a high acquisition option value in the negotiation with future investors. I model this as an increase in the current owners' outside option—instead of raising more capital, the owners can sell to a potential acquirer—allowing the current owners to retain a larger share of the surplus created from raising external capital.

7.1 Empirical Strategy

The hypothesis outlined in section 3 demonstrates that the incentives to cater to incumbents increase in scarcity of capital, implying that the magnitude of a firms' complementary innovations should increase with scarcity of capital, or equivalently decrease as capital availability increases. To test this hypothesis, I estimate a stacked difference-in-difference specification using a policy change that affected the inflow of new capital into the private equity markets—the implementation of the Prudent Person Rules (PPR) across US states. Specifically, I test whether *increasing* availability of capital leads to a *decrease* in the similarity of a startup firm's innovations.

The implementation of the PPR was staggered across US states following the adoption of the Uniform Prudent Investor Act (UPIA) in 1994 by the Uniform Law Commission. The PPR impacted all state pension funds not previously covered by the Employee Retirement Security Act implemented in 1979 and redefined the trustee's fiduciary duties. Prior to the PPR, the prudence of a trustee was evaluated at the level of an individual investment, rendering certain types of investments inherently imprudent. The implementation of PPR redefined prudence by emphasizing diversification and bringing the policy in line with modern portfolio theory. The "prudence" of risky individual investments, such as private equity (including VC), are evaluated within the overall portfolio. The policy enabled local state pension funds to extend their investing activities into alternative investments such as private equity, including VC. The timing of the implementation is spread across the years, as shown in fig. 6, starting in 1992 (Illinois) and ending in 2013 (Montana). The estimations only include the events in the $1996 - 2008$ period. Notably, this excludes California and New York, among others (both 1995). The implementation of PPR as an exogenous increase in VC capital inflows has been used previously by González-Uribe (2020) in estimating the probability of a given firm joining a VC's portfolio, with the ultimate objective to assess the exchange of innovation resources among portfolio firms.

I use the stacked difference-in-difference model in eq. (12) to explicitly test whether an increase in relative capital supply causes firms to adjust their innovation strategy.[27] I construct a cohort for each treated firm around the implementation of the PPR in their home state. A cohort (c) consists of treated firms in industry i and state s with at least one new introduction in the three years before the implementation and the four years after the new introduction.[28] The control group consists of firms in the same industry, defined as the Venturexpert highest industry subgroup, but located in a different state that did not adopt the PPR during a given time window. The firms in the control sample are also required to have new introductions in the window before and after the implementation of PPR in the treated state s. I estimate the model using ordinary least squares and include firm-cohort (ν_{ic}) and time-cohort (γ_{tc}) fixed effects. The dependent variable is either the portfolio-to-portfolio score ($Score_{iact}^{Portfolio}$) or the introduction-to-portfolio score ($Score_{iact}^{Introduction}$), where the former compares the startup firms stock of innovations (either patents or trademarks) after a new introduction to potential acquirers' stock of innovations, and the latter the inflows of innovations to the potential acquirers' stock.

$$Score_{iact} = \beta\big(Post_{ct} \cdot PPR_{ic}\big) + \nu_{ic} + \gamma_{tc} + \varepsilon_{iact} \tag{12}$$

The key identifying assumption is that absent treatment, the changes in the magnitude of complementarity of the firms in the treated group and the control group would have followed the same trend. Moreover, for the treatment to be *relevant*, firms in the treated group need to benefit relatively more from the policy change than the firms located in a different state in the control group. The implementation of the PPR in a state significantly increased inflows of capital from local state pension funds into local private equity funds, including VC and buyout funds.[29] For the treatment to be relevant, this increase in local capital flows should also disproportionately benefit local firms, and the local startups should perceive this increase as easing their search cost for future investors. Appendix A3 addresses the relevance of the treatment. Using the same

[27]A similar implementation is used in, e.g., Gormley and Matsa (2011) and the online appendix of Cengiz, Dube, Lindner and Zipperer (2019).

[28]I can expand this window to five years before and five years after. However, this does not materially expand the treated nor the control sample and does not change the results.

[29]González-Uribe (2020) provides evidence supporting this claim. Her results are consistent with the findings of, e.g., Hochberg and Rauh (2013), who document a significant home bias in public pension funds' private equity investments.

methodology (a stacked difference-in-differences design), I show that: (i) inflows into local VC funds increased following the event; (ii) investments by local VC funds increased following the event; and (iii) investments in local firms increased following the event.

The stacked event design has several benefits: the design enables the researcher to control the treatment window and the inclusion of firms in the control group, it is more robust to potential issues arising from heterogeneous treatment effects, and it works nicely with the structure of the data in this paper.[30] In the standard two-way fixed effects difference-in-difference estimator, past treated units are effectively used as control states when there are no or few never-treated observations. In the presence of heterogeneous treatment effects, this introduces bias that is especially severe in staggered specifications where the identification is based on the timing of the treatment. Moreover, the stacked difference approach is feasible for a highly unbalanced panel sample such as the data in this paper. Only the years in which a startup makes introductions are of interest, as the objective is to isolate changes in the similarity scores driven by the actions of the startup firm, even if it is possible to observe also years in which there are no observable changes in the startup's innovation portfolio.

Identification of the treatment effect relies on the staggered implementation of the PPR as an exogenous variation in the firm's perceived relative capital supply. The treatment effect captures the change in the treated startup firm's innovation strategy relative to the change in the innovation strategies of the startup firms in the control group. The flexibility and transparency enabled by the stacked design are reassuring as states with significant entrepreneurial and VC activity were generally early adopters. Most of the firms in the sample are located in states that adopted the PPR in the early '90s. Thus, the plausible set of control firms that never experienced treatment is small and sometimes non-existent. Therefore, the control group consists of firms located in states that have already experienced the adoption of the legislation, and the amount of time since the adoption is one of the criteria for inclusion in the control group that vary across the specifications.

The identifying assumption, the parallel trend assumption, requires that firms are not experiencing any different *trends* in the incentives to cater to potential acquirers prior to the treatment date, but the *level* of their catering propensity can be different. If "enough" time has passed

[30]The econometric literature has recognized the issues arising from heterogeneous treatment effects in two-way fixed effect difference-in-difference estimations, particularly in staggered treatment settings, and several corrections have been proposed (see, e.g., Athey and Imbens, 2021; Goodman-Bacon, 2021; De Chaisemartin and d'Haultfoeuille, 2020). Baker et al. (2021) review the recent advances and the suggested solutions, including the stacked approach applied in this paper.

since the policy adoption, the firms should have adjusted to the new normal, and capital market competition reached a new equilibrium.

To address this concern, I also estimate eq. (13), an extended version of eq. (12) where I interact the treatment variable PPR_{ic} with the full set of years relative to treatment. I_{ct} is an indicator variable for year t relative to treatment in cohort c. The year prior to the adoption of the policy ($t = -1$) serves as the baseline. If the parallel trend assumption holds β_t should not be different from zero if $t < 0$, while β_t should be negative after treatment.

$$Score_{iact} = \sum_{t \neq -1} \beta_t \big(I_{ct} \cdot PPR_{ic}\big) + \nu_{ic} + \gamma_{tc} + \varepsilon_{iact} \tag{13}$$

7.2 Results

The incentives to invest in complementary innovations should decrease following an increase in relative capital supply, suggesting that the estimate of β in eq. (12) should be negative. A negative β implies that firms introduce less complementary innovations. The results from the estimation of eq. (12) are reported in table 6 for both the trademark and patent samples. We should expect the magnitude of a firm's complementary innovation activities to decrease when capital availability increases. The coefficient estimate on $Post_{ct} \cdot PPR_{ic}$ is consistently negative in each specification and statistically significant in both samples for the portfolio-to-portfolio scores (columns 4-6 in the two panels in table 6) and in the patent sample for the estimates of the introduction scores. These results suggest that an increase in local capital flows has a negative causal impact on the magnitude of startup firms' complementary innovation activities. In the trademark sample, the estimates are consistently negative but statistically insignificant when the inclusion criteria in the trademark sample are less stringent, i.e., when the window since treatment criteria for inclusion in the control group is shorter.

The timing of the decrease coincides with the adoption of the PPR. Figure 7 shows the coefficient estimates of the extended version of the specification in eq. (13). While this is not definitive proof that the parallel trend assumption holds, it is at least reassuring. However, it is important to interpret these results with the details of the specification in mind. First, I report within startup firm estimates by requiring each firm to have at least one introduction before the treatment event as well as in the post-window. For most firms, this implies that they have only one or maybe two introductions in the pre-event and post-event window, respectively. In all specifications, excluding the trademark introduction specification, the estimate starts trending downward in the years following the adoption, suggesting that the firms have had more time to internalize the change when more time has passed. For the trademark introduction sample, the pre-trend is ambiguous, and confidence intervals are wide. The introductions are noisier in general than the portfolio scores and exhibit more variance in both the time series and the cross-section.

In the models with the portfolio scores as the dependent variable, the average post-treatment effect is statistically and economically significant and relatively stable to varying the length of the "no treatment window" (more stringent criteria implies a longer "no treatment window"). The results suggest that the level of complementarity for new introductions post-treatment is, on average, about $0.3 - 0.5$ lower for the trademark sample and about $0.8 - 0.85$ for the patent sample, corresponding to about a $1.4 - 2.4\%$ and 4.5% decrease in complementarity in the two samples, respectively. On average, firms that experience an increase in the relative capital supply decrease the level of complementarity in their innovation strategy relative to firms that do not experience the same decrease. The results thus support the hypothesis that a decrease in the relative attractiveness of being acquired decreases the startups' incentives to cater to incumbents, and firms adjust their innovation output accordingly.

Identification of the β estimator relies on the parallel trends assumptions and the relevance of the policy implementation as an instrument for increased relative capital availability. The results reported in table 6 are of a reduced form nature. The policy operates through an increase in capital inflows into the local VC market and the relative increase in the perceived capital market supply of local firms.[31] This has implications for the interpretation of the magnitude of β, as the average treatment effect on the treated should depend on the treatment effect on the local VC market, suggesting that the role of heterogeneous treatment effects are of concern in these estimates. The stacked approach addresses most of the biases this introduces when using the standard two-way fixed effects approach. However, it is worth bearing in mind that the reported estimates are an average treatment effect on the treated firms but, nonetheless, evidence in favor of the channel studied in this paper.

Results from additional robustness tests are reported in appendix A5. In table 6, the criteria for inclusion into the control group are relaxed and also include firms based in states that adopt the policy after the given time window. The patent sample is unaffected, but the trademark

[31] I provide empirical evidence in appendix A3 suggesting that local firms experienced a relative increase in access to VC capital.

sample increases marginally, and the results are quantitatively similar. In table table A.5.2 and table A.5.3, firms based in California or Massachusetts are excluded from both the treatment sample and the control group. Dropping these observations does not materially change the results. In the main specification, the standard errors are clustered at the state level to address the concern of serial correlation. The number of states included in the estimations is small, and the consistency of the reported standard errors is potentially biased downward. In appendix A5, I address this concern and present the results from a specification that corrects for serial correlation by collapsing the time series into a pre-and post-period. In Bertrand, Duflo and Mullainathan (2004), this approach is shown to be effective in samples with a small number of clusters.

7.3 Discussion

The results in this section support the notion that firms adjust their innovation strategy to changing incentives, specifically that firms introduce less complementary innovations when a future acquisition becomes relatively less attractive. The identification strategy relies on a critical assumption—a future exit as an independent company requires more external financing. Under this assumption, an increase in relative capital supply benefits the startup firm's current owners by improving their bargaining position in future financing rounds. The incentives to engage in complementary innovations that increase the expected payoff in an acquisition thus decrease. This exit path becomes relatively less attractive and requires costly efforts that negatively impact the return on an exit as an independent company. This mechanism is motivated in section 3.

While increased acquisition market activity can stimulate entrepreneurial entry and innovation output, this paper highlights a different consequence. As an exit by acquisition becomes relatively more attractive, the innovation strategy of startup firms becomes less independent of incumbent firms' innovation needs. The results in this section emphasize the role of financial markets and the structure of VC markets in shaping the direction of innovation of startup firms, even within the startup firm. I show that firms cater less to potential acquirers as VC becomes less scarce.

8 Conclusion

I study an important channel through which the increased prevalence of corporate acquisitions of young firms affects productivity and economic growth; how changes in the relative attractiveness of different exit modes shift VC financed startup firms' innovation incentives and causes firms to adjust their innovation strategy toward less independent innovations. I provide some empirical results highlighting the importance of acquisition market activity as a determinant of the direction of innovation of startup firms. Moreover, I show that as the relative attractiveness of staying independent increases, the magnitude of startup firms' complementary innovations decreases, and innovations become more independent of incumbent firms' assets. I use the staggered implementation of the Prudent Person Rules across US states to identify the causal effect. The results show that the availability of external capital and competition in VC markets is an important determinant for the types of innovations that startup firms develop. The paper also reveals an important externality of having well-developed private capital markets. Young firms rely on external financing, and when capital is more scarce, they have stronger incentives to cater to incumbents. I focus on the changes in the innovation strategy *within* firms and exploit the importance of the exit event for VC funds.

Moreover, the innovation measures developed in this paper can be extended to other samples of firms and be helpful when addressing other questions related to the direction of innovation. The publicly available data can be matched to any sample of firms and extends the scope of innovation activity studied in the economy along several dimensions relative to a project that only includes patent data.

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9 Figures

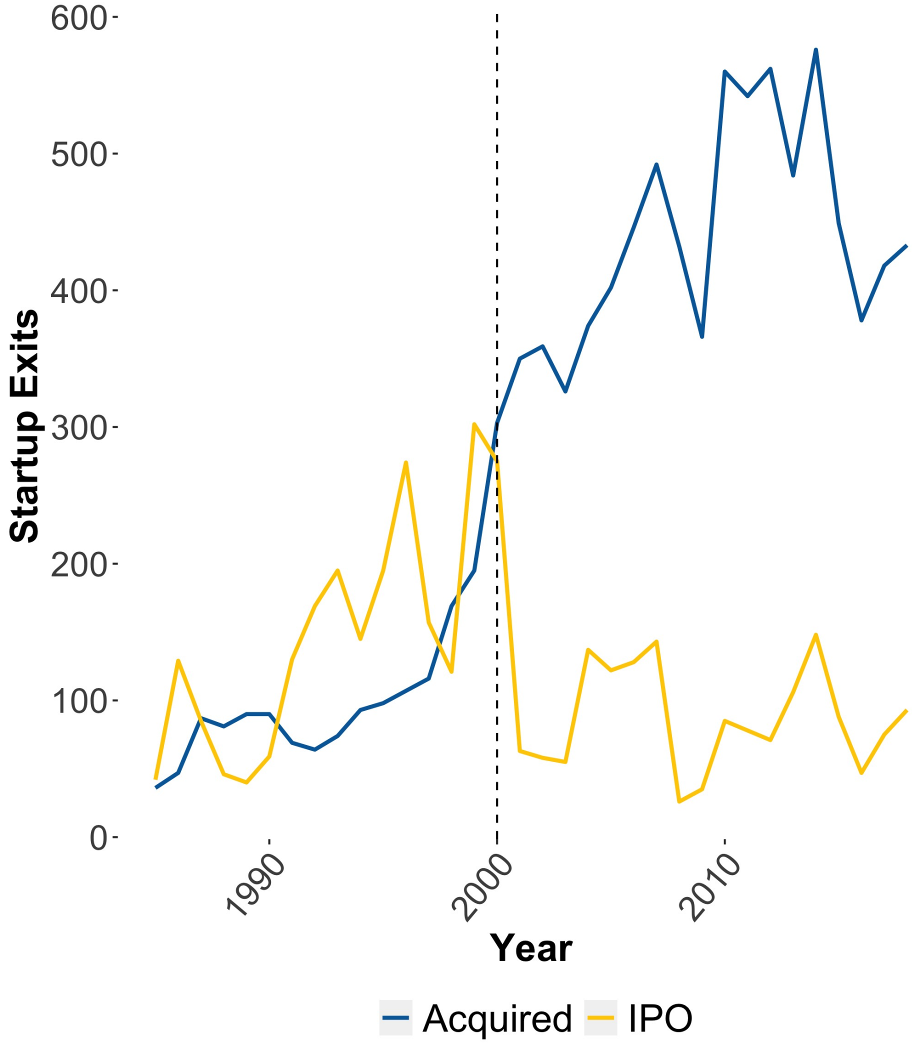

Figure 1: Time Trend Startup Exits Number of startup exits by IPO and acquisition in the Venturexpert sample of firms in year 1985–2018. The dotted vertical line is year 2000. Each firm is located in the US, founded after 1980, and has received at least one round of VC financing.

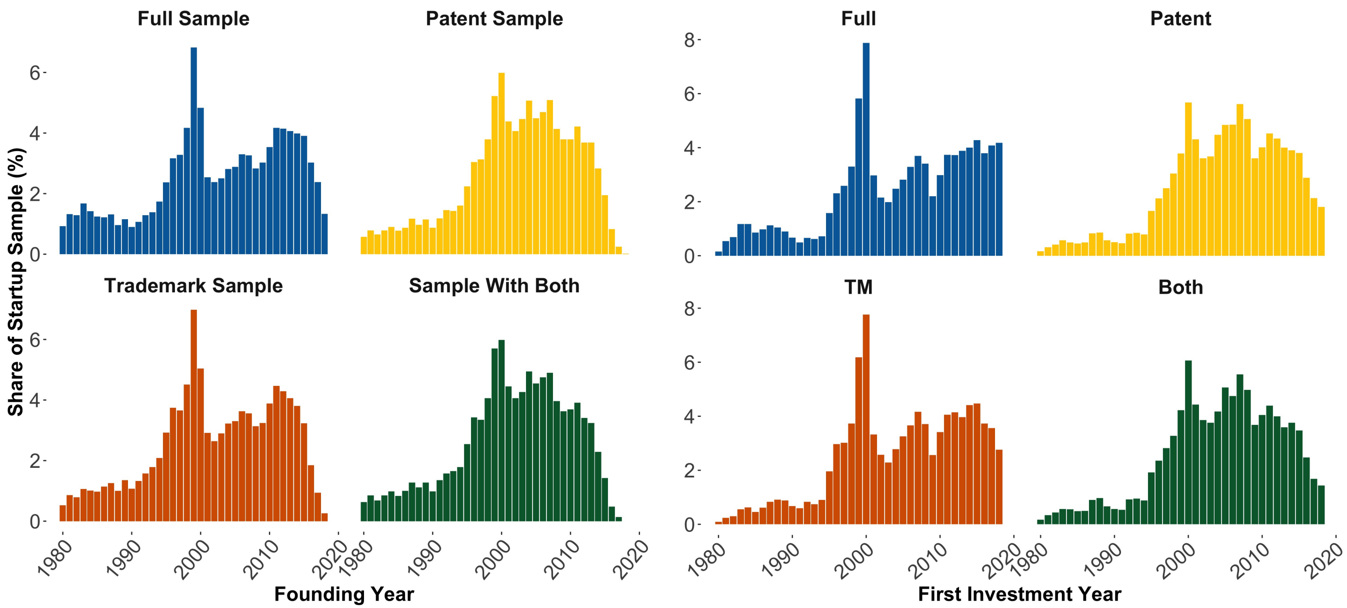

Figure 2: Age Distribution Startup Samples Distribution of the sample startup firms' founding year and year of first (VC) investment across the different samples/subsamples; the full sample of firms includes all startup firms in the original sample from Venturexpert, the trademark sample includes all startups that can be matched to at least one trademark and the patent sample includes the subset of startups that can be matched to at least one patent. The sample with both includes startups that can be matched to at least one trademark and at least one patent.

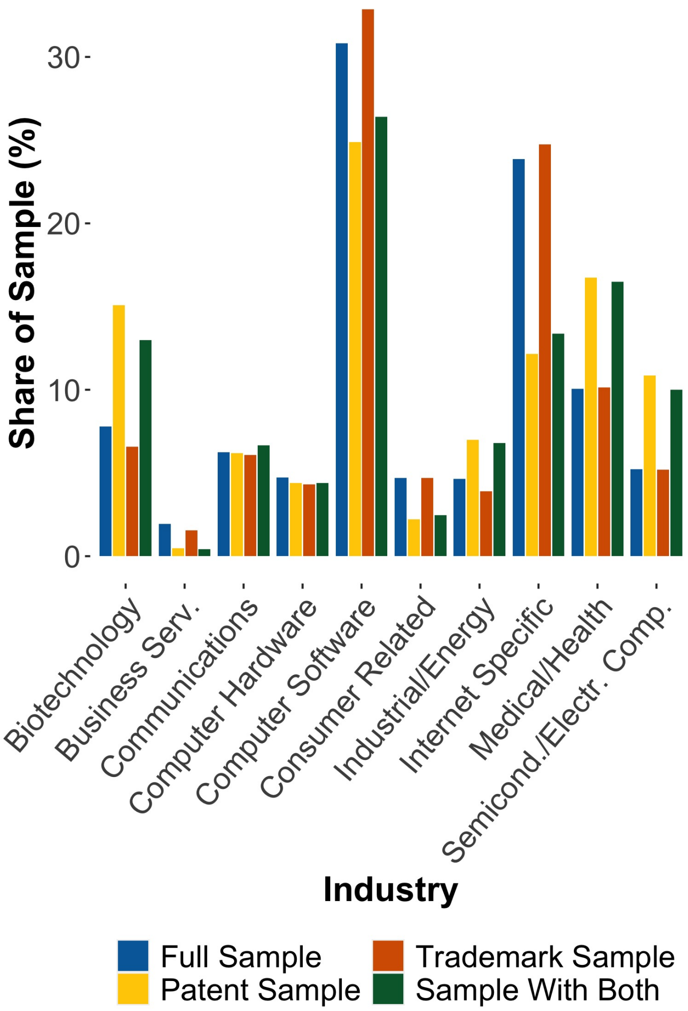

Figure 3: Industry Distribution Startup Sample This figure shows the industry distribution across the different samples/subsample; the full sample of firms includes all startup firms in the original sample from Venturexpert, the trademark sample includes all startups that can be matched to at least one trademark and the patent sample includes the subset of startups that can be matched to at least one patent. Sample with both includes startups that can be matched to at least one trademark and at least one patent.

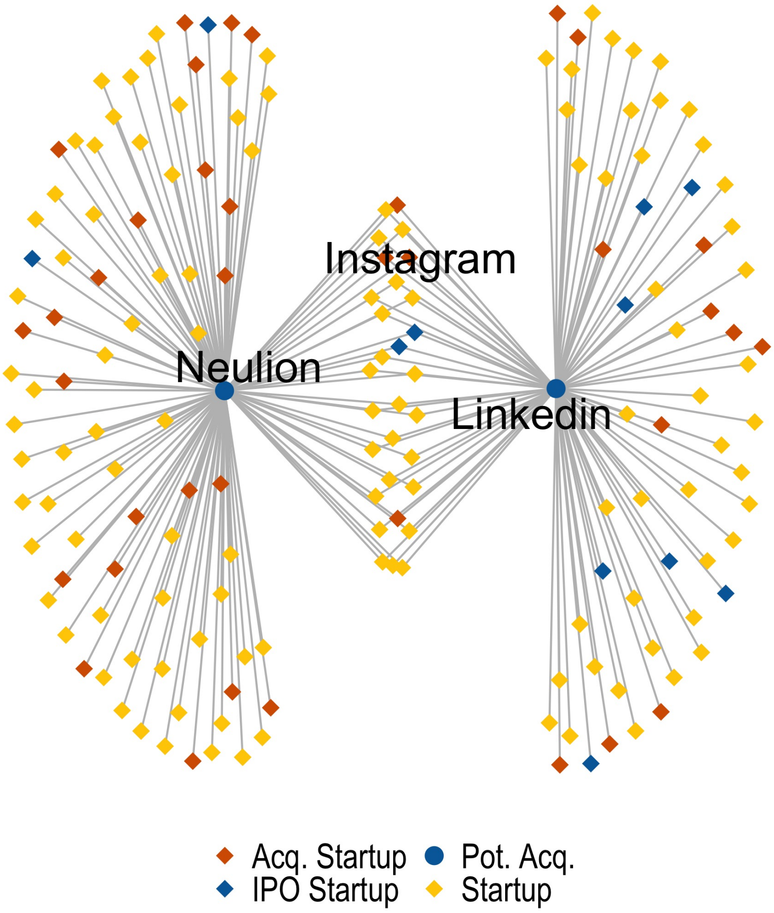

Figure 4: Measuring Acquisition Activity This figure illustrates the innovation network of two of Instagram's potential acquirers, Linkedin and Neulion. The blue circles represent the two potential acquirers. The diamond shapes represent startups with either Linkedin or Neulion as their potential acquirers in the years 2009 through 2011. The red diamonds are acquired by *someone*, not necessarily Linkedin or Neulion, in the years 2009–2011. The blue diamonds are startups that exited the sample by an IPO in the years 2009–2011. Among the startups with Linkedin as a potential acquirer 15 startups were acquired in the years 2009–2011. Linkedin's acquisition activity score in 2012 ($AA_{Linkedin,2012}$) equals $15/3 = 5$. For Neulion the number of acquisitions of related startups are 26 with ($AA_{Neulion,2012} = 26/3 \approx 8.67$).

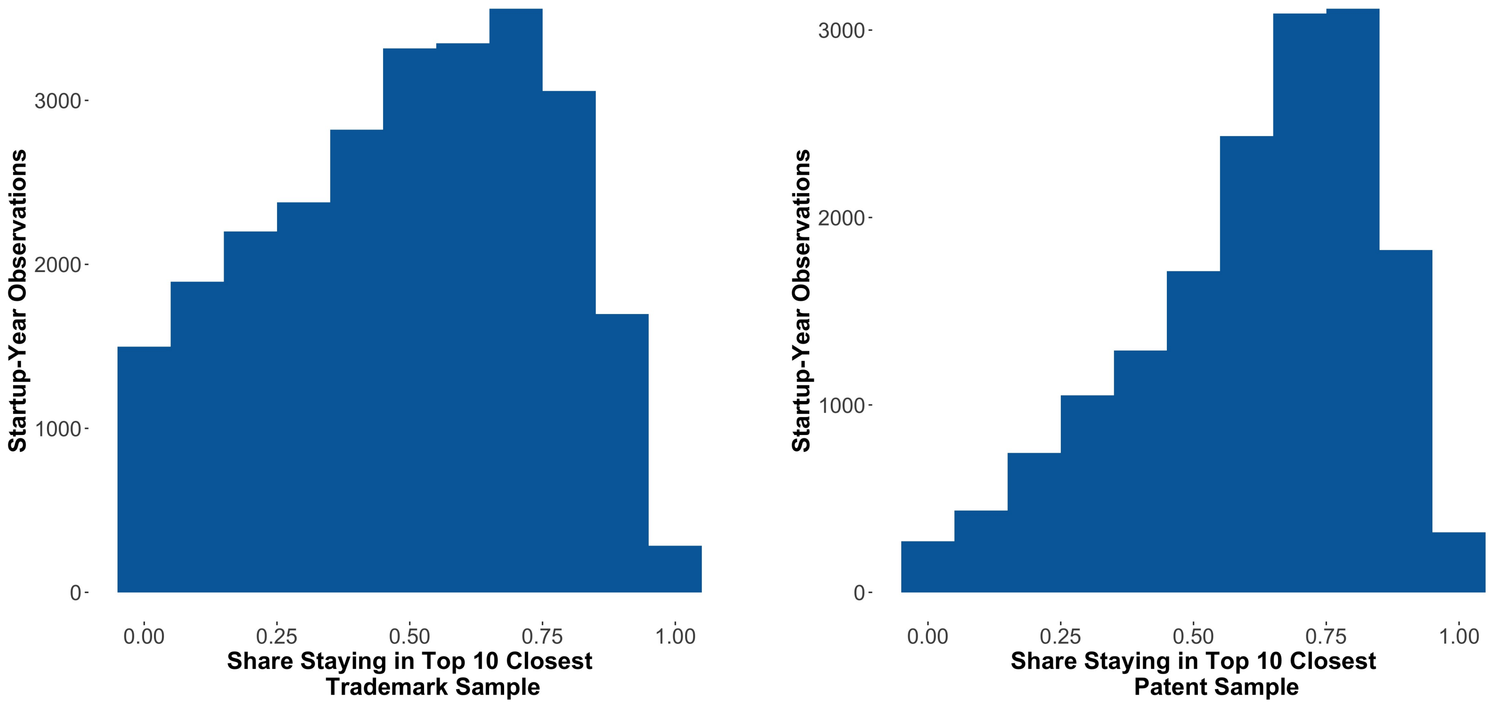

Figure 5: Turnover Closest Potential Acquirers This figure illustrates the turnover of the startups' top 10 closest potential acquirers in the trademark sample (left) and the patent sample (right). It plots the distribution of potential acquirers that remain among the top ten closest incumbents after a new introduction by the startup (e.g., after a new addition to the trademark portfolio or a new patent application).

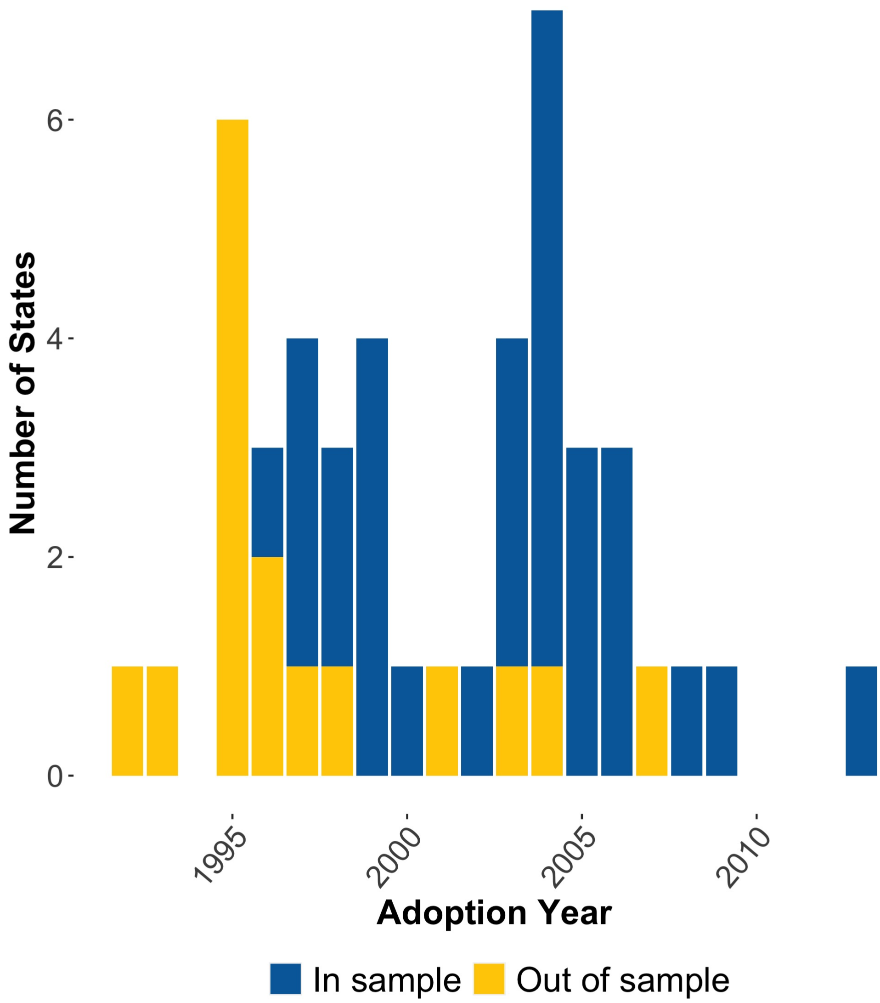

Figure 6: Timing of Policy Adoption This figure displays the timing of the adoption of the Prudent Person Rules across US states. The blue states represent adoption events that can be included in the treatment sample, while the yellow states cannot. Inclusion in the sample requires observing at least one startup firm with trademark/patent introductions both before and after the adoption in the treated state. In addition, there should be at least one plausible control firm for the treated firm according to at least one of the set of cohort criteria outlined in section 7.1. The state-industry combinations that eventually are included in the specifications depend on the specific inclusion criteria and vary somewhat across different specifications.

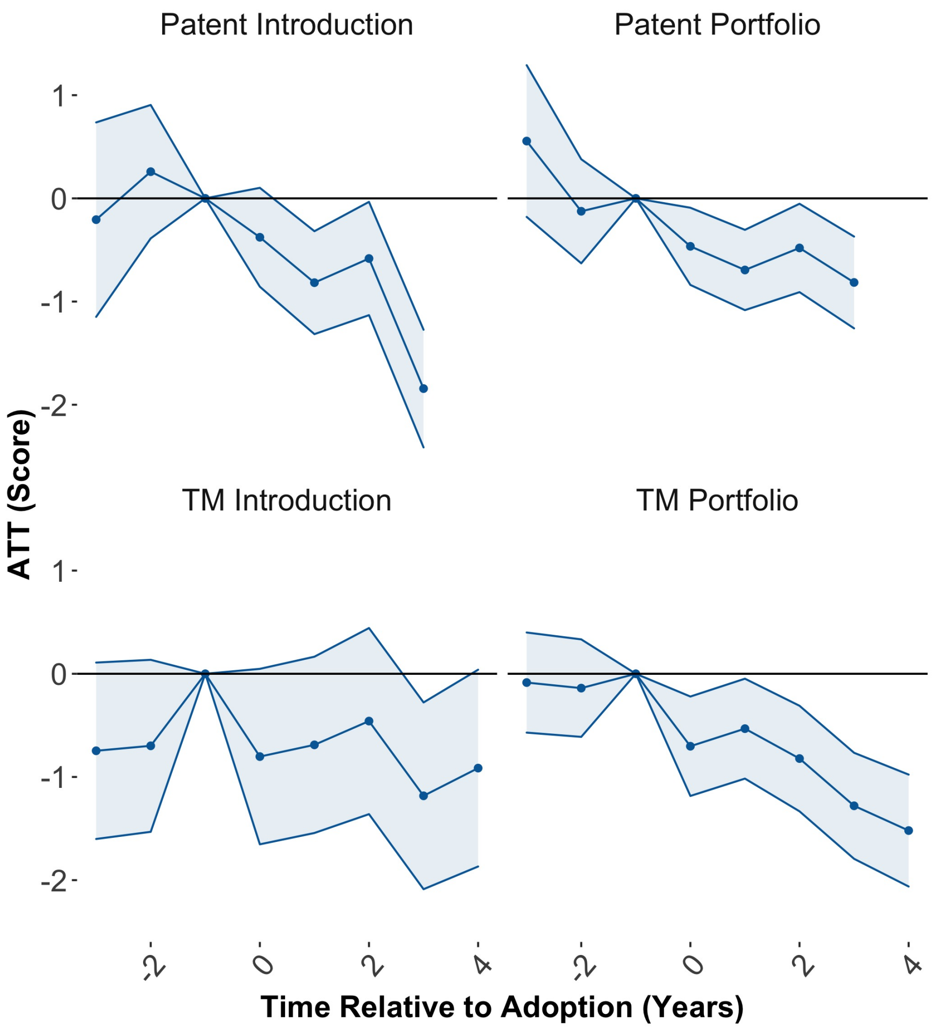

Figure 7: Extended difference-in-differences This figure presents estimates of an extended version of eq. (12) where the treatment effect is allowed to vary from year to year. I include all the years in the cohort sample (3 years prior to the treatment and 4 years post-treatment). Only 3 post-years are identified for the patent sample as no treated firms meeting the criteria have any introduction in the fourth year post-treatment. The year prior to the adoption of the PPR (Time = -1) constitute the baseline in the estimation. 95% confidence intervals using clustered standard errors at the state level are reported. The control group in the cohort consists of startup firms in a state where at least 7 years have passed since the adoption of the PPR.

10 Tables

Table 1: Descriptive Statistics Startup Samples This table shows the overlap between different samples split on whether the startup firm has trademarks or patents and the differences in exit outcomes across the samples. Success is the sum of IPO and Acquired. Failed include firms that are defunct, bankrupt, or in some way ceased to exist, as well as those firms where more than 10 years have passed since I observed any change to the firm. Most firms founded more recently remain Unresolved.

	All	With TM	With Patent	With TM and Patent
Firms	33,435	18,421	7,353	5,983
>1 Trademark yr (%)	33.41	60.63	60.06	73.81
>1 Patent year (%)	15.82	24.20	71.96	74.49
Success (%)	35.70	42.18	45.26	49.14
IPO (%)	9.44	12.10	18.94	21.61
Acquired (%)	26.27	30.08	26.32	27.53
Failed (%)	27.81	22.75	19.62	17.42
Unresolved (%)	34.69	32.80	32.73	30.85

Table 2: Descriptive Statistics Startup Life-Cycle This table describes differences over the startups' life cycles across the different samples. Panel A includes all startup firms with at least one trademark, Panel B all startup firms with at least one patent, and Panel C includes startup firms with at least one patent *and* at least one trademark.

Panel A: With Trademark	**N**	**Mean**	**Q25**	**Median**	**Q75**
Number of financing rounds	18,421	4.19	2	3	6
Age at first TM	18,421	2.91	1	2	4
Age at first investment	18,421	2.11	0	1	3
Number of Trademarks	18,421	6.47	2	3	6
Number of Trademark years	18,421	3.00	1	2	4
Panel B: With Patent					
Number of financing rounds	7,353	5.21	2	4	7
Age at first Patent	7,353	2.77	1	2	4
Age at first investment	7,353	4.94	1	3	7
Number of Patents	7,353	26.85	2	5	13
Number of Patent years	7,353	4.39	1	3	6
Panel C: With Trademark & Patent					
Number of financing rounds	5,983	5.48	3	5	7
Age at first Trademark	5,983	2.82	0	2	4
Age at first Patent	5,983	2.46	0	1	4
Age at first investment	5,983	5.17	1	3	7
Number of Trademarks	5,983	9.93	2	5	10
Number of Trademark years	5,983	4.16	1	3	5
Number of Patents	5,983	31.33	2	5	16
Number of Patent years	5,983	4.73	1	3	7

Table 3: Summary Statistics Panel A and B of this table presents summary statistics of innovation scores for each startup and year in which the startup introduced a new trademark or patent. It only includes the startup-potential acquirer pairs that are defined as previously close. Previously close potential acquirers are those who were among the top 10 closest after the most recent introduction. Panel C and D present summary statistics of the acquisition activity measure (AA_{at}) for the same observations as in Panel A and B. Full sample indicates the summary statistics across the entire sample. Max-Min is the summary statistics of the difference between the highest and the lowest score within each startup-year observation.

			Innovation Scores				
Panel A: Trademark	N	Mean	St. Dev.	Min	Q25	Q75	Max
$I(Staysintop10)_{iat}$	275,454	0.49	0.50	0	0	1	1
$Score_{iat}^{Portfolio}$	270,036	28.46	9.11	1.52	22.68	33.80	100.00
$Score_{iat}^{Introduction}$	275,454	21.08	13.26	0.00	12.33	28.87	100.00
Panel B: Patent							
$I(Staysintop10)_{iat}$	162,997	0.61	0.49	0	0	1	1
$Score_{iat}^{Portfolio}$	162,922	31.31	7.82	2.36	25.67	36.76	75.57
$Score_{iat}^{Introduction}$	162,997	18.35	4.86	0.00	15.17	21.36	61.26

				Acquisition Activity				
Panel C: Trademark	Mean	SD	Median	Min	Q25	Q75	Max	Share $AA_{at} = 0$
Full Sample	2.66	4.39	1	0	0.33	3.33	40.33	0.24
Max-Min	8.09	7.87	5.33	0	2.33	12	40.33	
Panel D: Patent								
Full Sample	2.29	2.81	1.33	0	0.33	3	21	0.14
Max-Min	5.58	4.31	4.33	0	2.33	8	21	

Table 4: Choice of Direction, Turnover This table displays results from a linear probability model estimating the probability that an acquirer a stays in the portfolio of startup firms i's closest acquirers. Only observations directly after an introduction by the startup are included. AA_{at} measures acquisition activity in the innovation area of potential acquirer a leading up to time t, specifically the 3-year lagged average. The control variables in columns (1) and (3) include the change in the flow of new funds into startup firm i's state and industry and how many financing rounds the firm has raised. Robust standard errors clustered at the potential acquirer level (a) are reported in parentheses.

	$I(StaysTop10)_{iat}$			
	Trademark		Patent	
AA_{at}	0.005***	0.004***	0.018***	0.016***
	(0.001)	(0.001)	(0.001)	(0.001)
Startup & year FE	Yes	No	Yes	No
Controls	Yes	No	Yes	No
Startup-year FE	No	Yes	No	Yes
Observations	269,031	269,051	159,864	159,864
R^2	0.158	0.291	0.135	0.227
Adjusted R^2	0.126	0.217	0.110	0.141

Note: *p<0.1; **p<0.05; ***p<0.01

Table 5: Choice of Direction, Magnitude This table displays results from a linear regression model with the similarity scores as the dependent variable. In columns (1) through (4), the dependent variable is $Score_{iat}^{Introduction}$, the similarity between startup i's new introduction (e.g., new additions to the trademark or patent portfolio) and the portfolio of a previously close acquirer a. In columns (5) through (8), the dependent variable is $Score_{iat}^{Portfolio}$, the similarity between startup i's portfolio (e.g., the portfolio of trademarks or patents held at the time) and the portfolio of a previously close acquirer a. The two dependent variables are described in detail in section 5. Only observations directly after an introduction by the startup are included. AA_{at} measures acquisition activity in the innovation area of potential acquirer a leading up to time t, specifically the 3-year lagged average. The control variables in columns (1), (3), (5), and (7) include the change in the flow of new funds into startup firm i's state- and industry-VC-market and how many financing rounds the firm has raised. Robust standard errors clustered at the potential acquirer level (a) are reported in parentheses.

	$Score_{iat}^{Introduction}$				$Score_{iat}^{Portfolio}$			
	Trademark		Patent		Trademark		Patent	
AA_{at}	0.224***	0.217***	0.128***	0.122***	0.059***	0.059***	0.111***	0.077***
	(0.009)	(0.007)	(0.005)	(0.004)	(0.005)	(0.004)	(0.006)	(0.003)
Startup & year FE	Yes	No	Yes	No	Yes	No	Yes	No
Controls	Yes	No	Yes	No	Yes	No	Yes	No
Startup-year FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	269,031	269,051	159,864	159,864	263,783	263,803	159,793	159,793
R^2	0.449	0.667	0.525	0.749	0.580	0.696	0.871	0.944
Adjusted R^2	0.428	0.632	0.512	0.721	0.563	0.664	0.868	0.938

Note: *p<0.1; **p<0.05; ***p<0.01

Table 6: Stacked Difference-in-Difference This table displays results from the estimation of a stacked difference-in-difference, using the sample of firms with trademarks (Panel A) and the sample of firms with patents (Panel B). The dependent variable in columns (1) through (3) are the similarity between startup i's new introduction and the portfolio of a previously close acquirer a ($Score_{iat}^{Introduction}$), and in columns (4) through (6) the dependent variable is the similarity between the startup's portfolio and the portfolio of the previous close potential acquirer ($Score_{iat}^{Portfolio}$). The sample of previously close firms is defined based on the scores after the last introduction. A cohort consists of treated firms located in states where the PPR was implemented and a control group of firms located in a state where adoption of PPR is before the "window". Only firms with at least one introduction in the 3 years leading up to the treatment and at least one introduction in the 4 years following the treatment year are included. All specifications include startup-cohort fixed effects and cohort-year fixed effects, and standard errors clustered at the state level are reported.

Panel A: Trademark	$Score_{iat}^{Introduction}$			$Score_{iat}^{Portfolio}$		
$Post_{ct} \cdot PPR_{ic}$	−0.326	−0.333	−0.508*	−0.641***	−0.846***	−1.060***
	(0.206)	(0.225)	(0.265)	(0.116)	(0.128)	(0.148)
Window	5	7	9	5	7	9
Observations	363,782	289,054	137,351	360,758	286,625	136,048
R^2	0.392	0.390	0.408	0.572	0.573	0.593
Adjusted R^2	0.374	0.372	0.388	0.560	0.560	0.580

Panel B: Patent	$Score_{iat}^{Introduction}$			$Score_{iat}^{Portfolio}$		
$Post_{ct} \cdot PPR_{ic}$	−0.805***	−0.836***	−0.852***	−0.622***	−0.609***	−0.489***
	(0.170)	(0.170)	(0.174)	(0.131)	(0.133)	(0.137)
Window	5	7	9	5	7	9
Observations	108,569	98,036	82,934	108,545	98,016	82,917
R^2	0.442	0.430	0.425	0.887	0.886	0.884
Adjusted R^2	0.428	0.417	0.411	0.885	0.883	0.881

Note: *p<0.1; **p<0.05; ***p<0.01

Appendices

A1 Detailed Note: Constructing the Measures

To measure the general complementarity of a firms' assets with assets in the economy, I use a text-based measure representing similarity with two different text sources: the claims section of patents from USPTO Bulk Data Storage and the goods and services description of the trademarks in the USPTO Trademark Case File dataset.

I define the trademark and patent portfolio as all the patents and trademarks (respectively) that a firm owns at a given point in time. This includes all the patents where the firm is the assignee and includes those introduced by the firm themselves and those acquired (to the extent that my matching of firms to the USPTO data is complete). A new introduction is either a new patent or a new trademark where the firm is the first assignee. For trademarks, I use the date of first use (in commerce) to identify the timing of the introduction. One trademark can span several "first use years" for different goods and services. For patents, I use the application date but only include granted patents.

I extract the text from the claims section in each patent and the goods and services description from the trademarks. These represent the text corpus of a new patent/trademark introduction. As I construct yearly measures, I aggregate the text of all patent/trademarks introduced in a given year into one text corpus. The text corpus of the respective portfolios is the accumulated text of all trademarks or patents assigned to the firm at a given point in time. This generates a panel of patent/trademark portfolios and a panel of new patent/trademark introductions.

I then compute the cosine similarity between:

- the patent portfolios of two firms,
- the trademark portfolios of two firms,
- the new patent introduction of firm a and the patent portfolio of firm b, and
- the new trademark introduction of firm a and the trademark portfolio of firm b.

I do not compare trademarks to patents as the nature of the text is very different. Hoberg and Phillips (2010) use cosine similarity of two firms 10-K product description files and show that the incidence of mergers and acquisitions increases in product similarity and that differentiation with respect to the acquirers' competitors improve the ex-post performance. Bena and Li (2014) use patent count and citation-based measures to show that probability of an acquisition and post-transaction innovation output increase in the overlap. Their innovation measure and empirical results are all computed at the firm pair level.

I compute these measures in three distinct steps

1. Construct word count vector for all firm-year observations (portfolios or new introductions).
2. Construct common word count vector for all firm-year observations (portfolios or new introductions).
3. Compute the firm pair-year similarity score.

A1.1 Word count vectors

I construct word indicator vectors for each firm-year for both portfolios and new introductions from the text corpus. The text corpus is translated into a vector representation where each element represents a word. The element is set to one if the word is used in the firm's text corpus. If a firm has no introductions in a given year, the word vector is fully populated by zeros. I construct word indicator vectors for each firm in all years after their first observed patent/trademark assignment or introduction. Trademarks are included in the portfolio from the date of first use for as long as the trademark is live. A patent is included in the text corpus from the date of application until expiration.

I drop all words that are defined as stop words by the *stop_words* dataset from the R library *tidytext*, a dataset that encompasses four different stop word libraries. I also drop "words" that are only comprised of special characters or numerics.

For each observation, I then compute the number of words used in the patent/trademark text as the sum of all elements in the word indicator vector. I construct two word count vectors (N_{VX} and N_{Comp}) where each element $n_{i,t}$ represents the number of words used by firm i (either in the sample from Venturexpert (the startups) or Compustat firms (potential acquirers)) in year t.

A1.2 Common word count vectors

I compute the common word count of a firm pair i, j in year t, where firm i is a startup firm and firm j a potential acquirer by taking the dot product of their respective word indicator vectors. I do this for all possible firm pairings in the panels in a given year t where the overlap is non-zero. I then construct a common word count vector (C) where one element ($c_{i,j,t}$) represents the number of common words in the respective corpora.

A1.3 Firm pair score

I compute the cosine similarity of scores (ignoring how many times a word is used in the text corpus) by joining the common word count vector C with the word count vectors. The firm pair-quarter measure of complementarity is then computed as:

$$s_{i,j,t} = \frac{I_{i,t} \cdot I_{j,t}}{\|I_{i,t}\|\|I_{j,t}\|} = \frac{\text{Common words}_{i,j,t}}{\sqrt{\text{Distinct words in text}_{i,t} \cdot \text{Distinct words in text}_{j,t}}} \tag{A.1.1}$$

The expression in eq. (A.1.1) is the cosine similarity between the two word indicator vectors. The cosine similarity is a commonly used measure of similarity between two text corpora. Implementing the word indicator vectors rather than word frequency vectors is motivated by the ease of computation. This implementation of cosine similarity is used by, e.g., Hoberg and Phillips (2010, 2016).

A2 Similarity Scores Over the Startup Life-Cycle

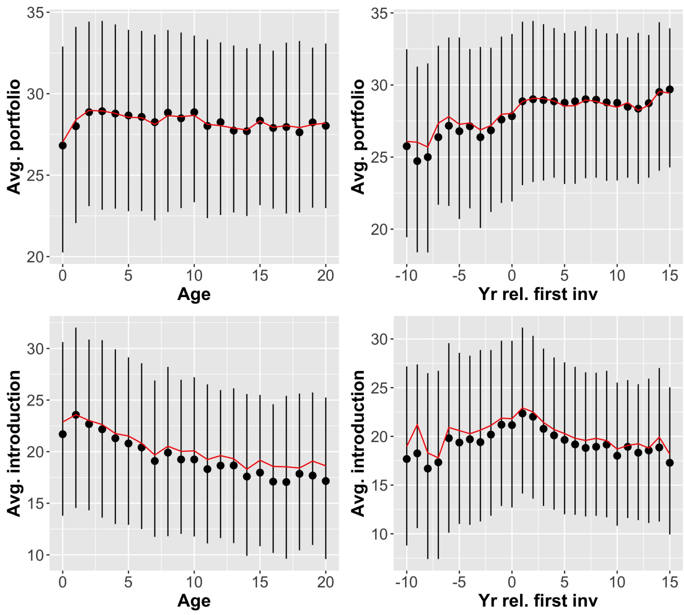

Figure A.2.1: Lifecycle Scores: Trademark Average trademark portfolio and introduction score after a new introduction by the startup. Only the scores relative to the top 10 closest prior to the new introduction are included.

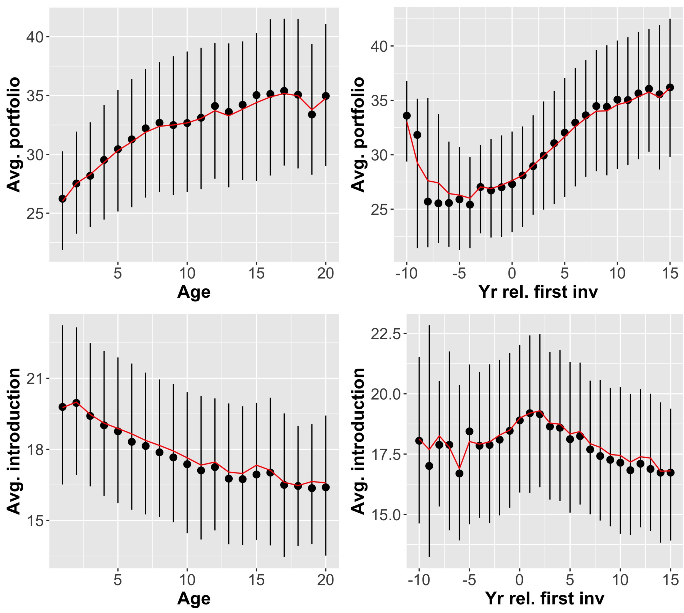

Figure A.2.2: Lifecycle Scores: Patent Average patent portfolio and introduction score after a new introduction by the startup. Only the scores relative to the top 10 closest prior to the new introduction are included.

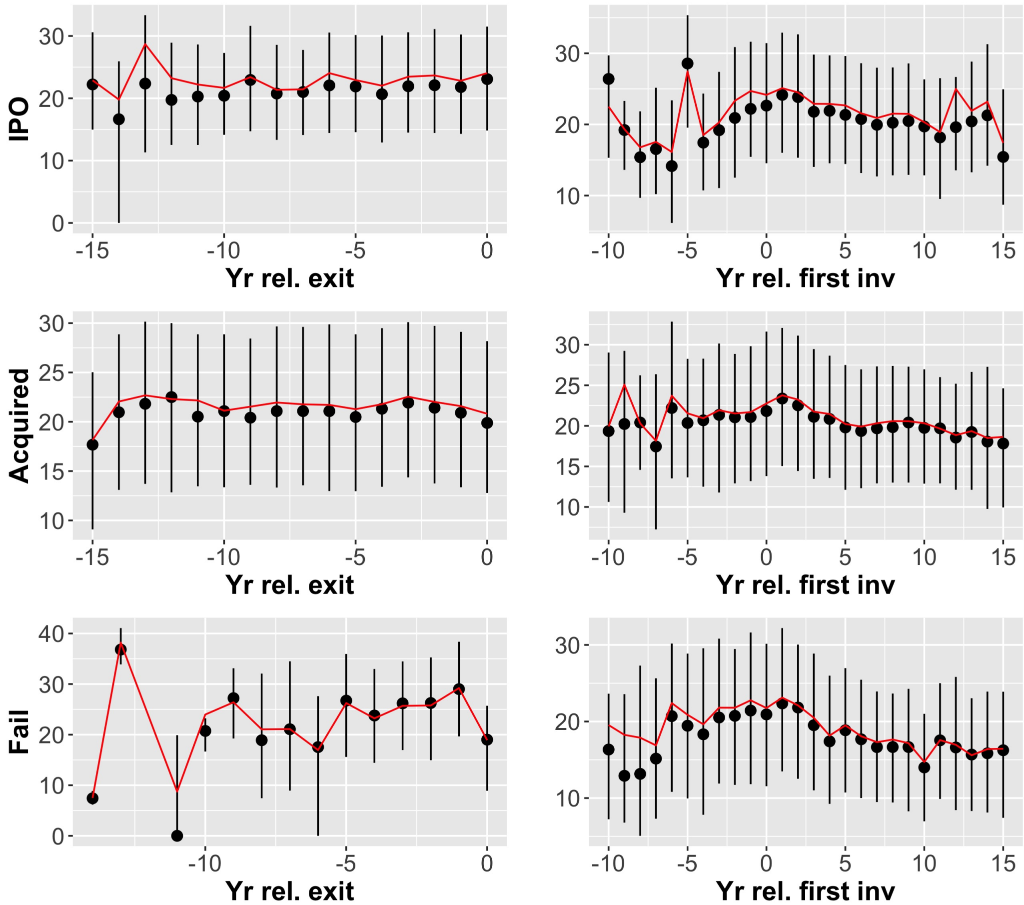

Figure A.2.3: Lifecycle Scores by Exit: Trademark Average trademark introduction score by the startup split by exit mode. Only the scores relative to the top 10 closest prior to the new introduction are included.

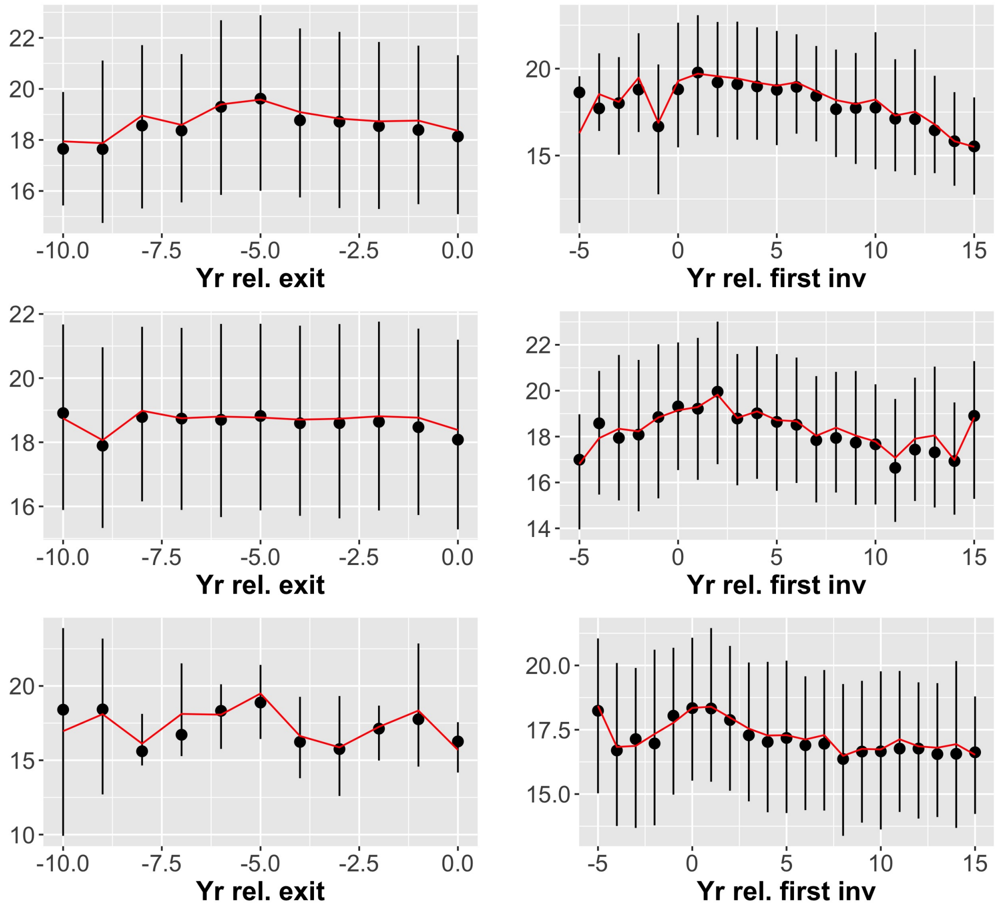

Figure A.2.4: Lifecycle Scores by Exit: Patent Average patent introduction score by the startup split by exit mode. Only the scores relative to the top 10 closest prior to the new introduction are included.

A3 Changes in Capital Supply

In this appendix, I perform the same analysis as in section 7 but with state-industry VC inflows and state-industry number of VC investments as the dependent variable. Specifically, I estimate the equation in eq. (A.3.1) where Y_{jct} is the VC inflows in state s and industry j in year t, where c represent the cohort. The cohorts are constructed as in section 7. For each industry in the treated state, I construct a control sample of observations in the same industry where the PPR has not been implemented during the seven years leading up to nor in the seven years after the treatment year in the treated state. I include both industry, state, and year fixed effects to control for unobserved heterogeneity and allow the fixed effects to vary by cohort to control for additional time heterogeneity.

$$Y_{jstc} = \beta\big(Post_{ct} \cdot PPR_{jc}\big) + \nu_{jc} + \eta_{sc} + \gamma_{tc} + \varepsilon_{iact} \tag{A.3.1}$$

The results are presented in table A.3.1 with both the level and log of the dependent variables. The average post-treatment effect is statistically and economically significant. Columns (2) and (4) suggest that the average treatment effect on fund flows into VC funds ($) and local investments (number of investments in local startups) is about 14.4% and 16%, respectively.[32] The average treatment effect on the level of investments by local VC firms is however lower, approximately 2.3%. There are several possible explanations for the discrepancy between the dollar level of investments by and fund flows into local VC firms. First, fund flows occur before investments and the effect should be visible later in the data. While extending the window studied would be possible, the observations eligible for inclusion in the control group would become very small. Second, investments have a much lower data coverage, and some VC funds have no recorded investments, which could bias the results if investment data is more likely reported in states in the control group.

$$Y_{jstc} = \sum_{\tau=-4}^{\tau=5} \left(\beta_\tau \big(I_{c\tau} \cdot PPR_{jc}\big)\right) + \nu_{jc} + \eta_{sc} + \gamma_{tc} + \varepsilon_{iact} \tag{A.3.2}$$

[32]The percentage impact on the dependent variable is approximately given by $100(e^{(\beta - \frac{1}{2}\hat{\sigma^2_\beta})} - 1)$

Secondly, the results from estimating eq. (A.3.2) are illustrated in fig. A.3.3 and fig. A.3.2. This is the same specification as in eq. (A.3.1), but extended to estimate the coefficient on each time period. The baseline is the year right before the adoption of the legislation ($t = -1$). There is no clear trend prior to the adoption, but the coefficient starts trending upwards after the adoption.

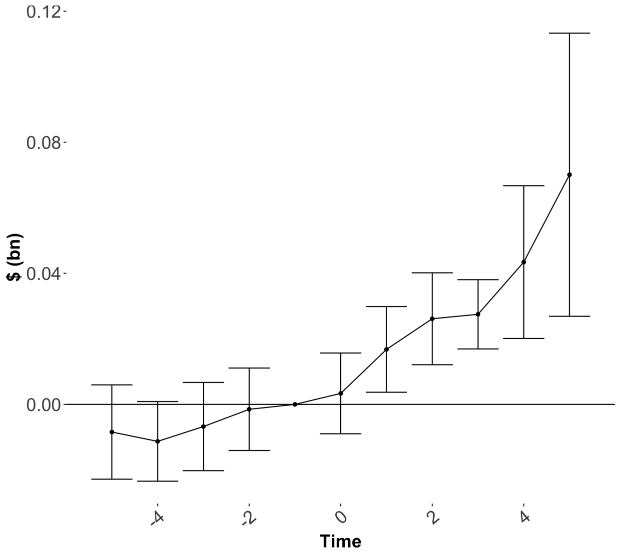

Figure A.3.1: VC Investments This figure illustrates estimates of the coefficient on post-treatment for difference-in-difference estimates using a similar methodology as described in section 7 but with the amount of investments in an industry j, by VC's located in a state s as the dependent variable. 95% confidence intervals are presented with standard errors clustered at the industry-year level.

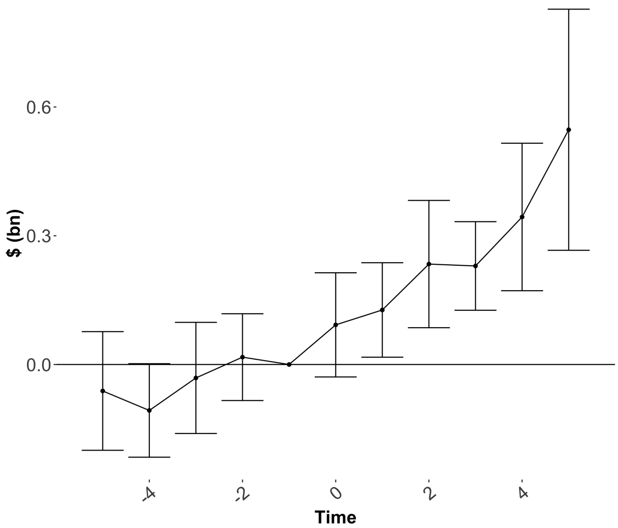

Figure A.3.2: VC Inflows This figure illustrates estimates of the coefficient on post-treatment for difference-in-difference estimates using a similar methodology as described in section 7 but with industry-state VC inflows as the dependent variable. 95% confidence intervals are presented with standard errors clustered at the industry-year level.

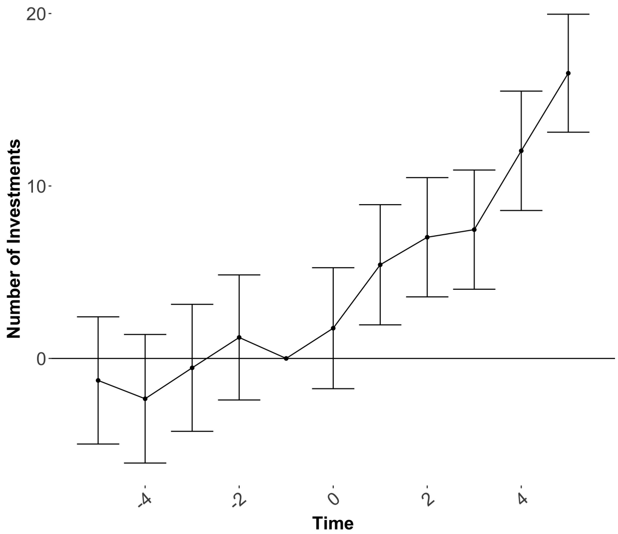

Figure A.3.3: Investments in Startup Firms This figure illustrates estimates of the coefficient on post-treatment for difference-in-difference estimates using a similar methodology as described in section 7 but with the number of (VC) investments in local firms in an industry and state as the dependent variable. 95% confidence intervals on the estimators are presented with standard errors clustered at the industry-year level.

Table A.3.1: Relevance: Difference-In-Difference This table displays results from the estimation of a stacked difference-in-difference. The dependent variable is capital inflows into VC funds, investments (in $) by VCs located in a given state, and the number of investments by (any) VC's in a state, including those located elsewhere, at the industry-state level. The treated group consists of state-industry observations where the Prudent Person Rule (PPR) was implemented in the state. The control group consists of state-industry observations where the state has not implemented the PPR in the 7 years before the implementation in the treated state. All specifications include state-cohort, industry-cohort, and year-cohort fixed effects, and standard errors clustered at the industry-cohort level are reported.

	VC Inflows		VC Investments		Startup Investments	
	Level	Log	Level	Log	Level	Log
$Post_{ct} \cdot PPR_{jc}$	0.275***	0.145***	0.036***	0.027***	9.030**	0.167***
	(0.060)	(0.021)	(0.012)	(0.008)	(3.546)	(0.038)
Industry-cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
State-cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,957	7,957	20,366	20,366	20,347	20,347
R^2	0.508	0.647	0.505	0.608	0.653	0.829
Adjusted R^2	−0.140	0.183	0.319	0.461	0.459	0.733

Note: *p<0.1; **p<0.05; ***p<0.01

A4 Mini Case: Instagram

Instagram was founded at the beginning of 2010 by Kevin Systrom. The original product, developed by Systrom, was a mobile application known as "Burnbn" that allowed for geotagged photo and note sharing.[33]. In March 2010, the company closed its first financing round, raising $500, 000 from Baseline Ventures and Andreessen Horowitz. Both the founding year and the initial seed round are correctly recorded in the Venturexpert data used in this paper. Kriger joined after the launch of the Burnbn app, and later the two co-founders refocused the mobile application on photosharing services and renamed the company Instagram.

The company closed a $7 million early-stage capital round in February 2011 and $50 million in growth capital in April 2012, where, among others, Sequoia, Benchmark Capital, and Greyhound Partners invested in Instagram. On April 9th, 2012, Facebook announced the acquisition of Instagram, right before the Initial Public Offering by Facebook in May, and the deal officially closed on September 6th.[34]

At the time of the announcement of the acquisition, Instagram had no patents, nor had they ever filed for a patent. However, they had filed for several trademarks. In total, I observe 23 distinct trademarks (serial numbers) with a goods and services statement where the date of first use in commerce falls before the date of the announcement. For the purposes of the aggregation in this paper, this corresponds to three trademark observations before Instagram exits the sample. In total, I can observe eight distinct trademark year observations and 70 distinct trademarks (serial numbers) that meet the criteria, including those after Instagram exits the sample. This case thus highlights an essential contribution of this paper; by measuring innovation activity using only patenting activity, a large scope of innovative activity is ignored. While the inclusion of trademarks does not give a complete picture, it certainly increases the scope.

Figure A.4.1 presents the number of distinct words in all introductions in a given year, and the words are listed in table A.4.1. The figure represents the observational unit of introductions, while the table describes the evolution of the portfolio. For example, the word "computer" is used in 57 and "software" in 44 of all 70 trademarks but is only counted once per year in fig. A.4.1 and only shown once in table A.4.1.

[33]E.g., `https://www.inc.com/30under30/2011/profile-kevin-systrom-mike-krieger-founders-instagram.html`.

[34]See, e.g., `https://techcrunch.com/2012/09/06/facebook-closes-instagram-acquisition-instagram-announces-5-billion-photo` This date corresponds to the date of the acquisition in the data from Venturexpert.

The portfolio scores included in the analysis are presented in table A.4.2. Instagram made its first observed introduction in 2010. The portfolio and introduction score coincides in the first year, and therefore only the portfolio score is reported. I only report the scores if the firm was among the top ten closest at the time of the previous introduction. Facebook is among the top closest, as are other social media companies such as Twitter, LinkedIn, and The Meet Group. Companies that drop out of the portfolio operate within the social media/platform industry but with a different focus. Following the second year of introductions, the two companies that drop out are platform-based and mobile games developer Zynga (e.g., Farmville) and digital marketing company Local Corp (now delisted from Nasdaq). Box Inc., a cloud-based tool for content management and file sharing, and enterprise software solutions provider Deltek, are replaced by these companies.

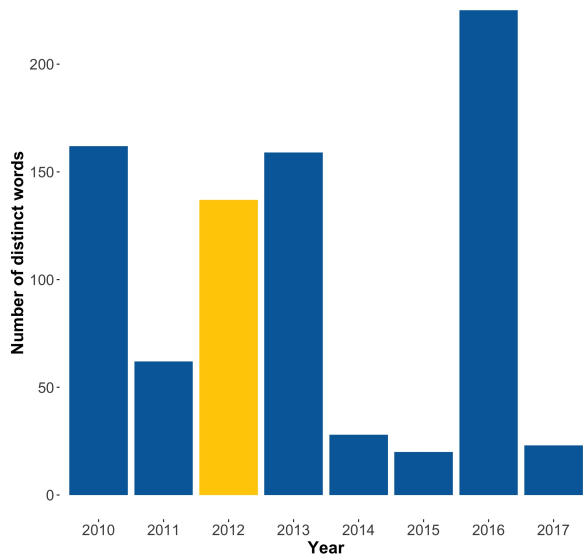

Figure A.4.1: New introduction word count: Instagram This figure shows the number of distinct words in the new introductions each year. The words are from the goods and services section and have been cleaned with the same procedure employed in the paper.

Table A.4.1: Instagram words This table shows the words added to Instagram's trademark portfolio in a given year. The words are from the goods and services section and have been cleaned with the same procedure employed in the paper. If a word already existed in the portfolio, it is not listed.

Year	Words
2010	ability, access, accessing, accounts, advice, allowing, api, appearance, application, applications, asp, audio, audiovisual, based, blogging, boards, broadcasting, building, bulletin, business, chat, collection, communication, communications, communities, community, computer, conducting, content, create, creating, customized, customizing, data, databases, dating, defined, desk, digital, discussions, displaying, distributing, documents, download, downloadable, downloading, editing, electronic, electronically, enable, enables, enabling, engage, engines, entertainment, events, facilitate, facilitates, facilities, featuring, field, fields, file, files, filtering, form, forums, generated, global, graphics, hosting, identity, images, including, indexes, information, instructions, interactive, interface, internet, introduction, journals, line, linking, links, local, logs, mail, manage, management, managing, marketing, media, meetings, messages, mobile, modifying, multiple, nature, network, networking, networks, obtaining, online, organizing, page, pages, participate, peer, personal, photo, photograph, photographic, photographs, photos, posting, profiles, programming, provided, provider, providing, provision, publication, publications, publishing, registered, retrieval, saas, search, searchable, service, services, share, sharing, site, sites, social, software, storage, streaming, support, tagging, technical, technology, telecommunications, temporary, text, topics, transfer, transmission, transmitting, upload, uploading, user, users, video, videos, virtual, visual, web, website, websites
2011	arrange, articles, blogs, creation, gatherings, participation, people
2012	applying, change, filters
2013	advertisements, advertising, clothing, consultation, dissemination, jackets, market, promoting, promotion, research, reviewing, shirts, sweat, telecommunication, tops, women
2014	bags, bottles, empty, pens, sold, storing, tote, umbrellas, water
2016	adhesive, alerts, analyzing, animations, annotating, apis, ar, augmented, blank, buying, campaigns, caps, capturing, chains, chatroom, children, commenting, comments, date, delivery, design, designing, developing, development, disseminating, drawings, edit, effects, email, embedding, engine, equipment, feed, finding, gift, hats, headwear, indicating, instant, interact, interacting, interfaces, key, kiosks, location, matter, message, messaging, note, notifications, optimizing, paas, paper, platform, platforms, printing, publishers, purchasing, reality, receiving, related, reminders, rental, reporting, searching, selling, sending, sentiment, stickers, subject, subscribe, subscribing, targeting, tracking, valuing, view, viewing
2017	means, special

Table A.4.2: Instagram Scores This table presents all the scores included in the analysis for Instagram Inc., i.e., the portfolio-to-portfolio score ($Score_{iat}^{Portfolio}$) after their first introduction in 2010 relative to the top 10 closest Compustat firms, as well as the introduction-to-portfolio score ($Score_{iat}^{Introduction}$) for the same set of firms. The portfolio scores are all computed based on the cumulative portfolio of words in Instagram's portfolio from inception until the end of the year, while the introduction scores are based on the accumulated words in all introductions in the given year.

	Portfolio			Introduction	
	2010	2011	2012	2011	2012
Facebook Inc.	53.92	53.88	52.15	25.82	49.52
The Meet Group Inc	54.33	51.82	51.36	34.32	55.71
Neulion Inc.	48.89	48.41	47.99	30.57	46.69
Tripadvisor Inc.	44.89	45.24	46.28	32.51	43.83
Liveperson Inc.	48.26	46.34	45.94	35.83	46.98
Linkedin Corp.	48.51	46.90	45.74	28.61	45.53
Box Inc.		48.22	45.29		43.90
Broadvision Inc.	44.79	44.37	43.98	34.10	46.10
Twitter Inc.	43.69	50.12	43.40	25.69	40.02
Deltek Inc.		43.60	43.21		43.79
Local Corp	42.14	42.87		34.33	
Zynga Inc.	44.11	41.68		28.57	

A5 Robustness Tests

Table A.5.1: Stacked Difference-in-Difference—Wider Control Group This table displays results from the estimation of a stacked difference-in-difference, using the sample of firms with trademarks (Panel A) and the sample of firms with patents (Panel B). The dependent variable in columns (1) through (3) are the similarity between startup i's new introduction and the portfolio of a previously close acquirer a ($Score^{Introduction}_{iat}$), and in columns (4) through (6) the dependent variable is the similarity between the startup's portfolio and the portfolio of the previous close potential acquirer ($Score^{Portfolio}_{iat}$). The sample of previously close firms is defined based on the scores after the last introduction. A cohort consists of treated firms located in states where the PPR was implemented and a control group of firms located in a state where adoption of PPR is outside the "window", either before or after. Only firms with at least one introduction in the 3 years leading up to the treatment and at least one introduction in the 4 years following the treatment year are included. All specifications include startup-cohort fixed effects and cohort-year fixed effects, and standard errors clustered at the state level are reported.

Panel A: Trademark	$Score^{Introduction}_{iat}$			$Score^{Portfolio}_{iat}$		
$Post_{ct} \cdot PPR_{ic}$	−0.222	−0.333	−0.769***	−0.286***	−0.435***	−0.751***
	(0.185)	(0.203)	(0.246)	(0.105)	(0.115)	(0.137)
Window	5	7	9	5	7	9
Observations	387,493	297,607	140,932	384,345	295,131	139,594
R^2	0.397	0.387	0.403	0.579	0.573	0.591
Adjusted R^2	0.379	0.369	0.384	0.567	0.560	0.578
Panel B: Patent	$Score^{Introduction}_{iat}$			$Score^{Portfolio}_{iat}$		
$Post_{ct} \cdot PPR_{ic}$	−0.805***	−0.836***	−0.852***	−0.622***	−0.609***	−0.489***
	(0.170)	(0.170)	(0.174)	(0.131)	(0.133)	(0.137)
Window	5	7	9	5	7	9
Observations	108,569	98,036	82,934	108,545	98,016	82,917
R^2	0.442	0.430	0.425	0.887	0.886	0.884
Adjusted R^2	0.428	0.417	0.411	0.885	0.883	0.881

Note: *p<0.1; **p<0.05; ***p<0.01

Table A.5.2: Stacked Difference-in-Difference—Excluding States This table displays results from the estimation of a stacked difference-in-difference, the same regression as in table 6 but excluding any observations from California and Massachusetts, using the sample of firms with trademarks (Panel A) and the sample of firms with patents (Panel B). The dependent variable in columns (1) through (3) are the similarity between startup i's new introduction and the portfolio of a previously close acquirer a ($Score_{iat}^{Introduction}$), and in columns (4) through (6) the dependent variable is the similarity between the startup's portfolio and the portfolio of the previous close potential acquirer ($Score_{iat}^{Portfolio}$). The sample of previously close firms is defined based on the scores after the last introduction. A cohort consists of treated firms located in states where the PPR was implemented and a control group of firms located in a state where adoption of PPR is before the "window". Only firms with at least one introduction in the 3 years leading up to the treatment and at least one introduction in the 4 years following the treatment year are included. All specifications include startup-cohort fixed effects and cohort-year fixed effects, and standard errors clustered at the state level are reported.

Panel A: Trademark		$Score_{iat}^{Introduction}$			$Score_{iat}^{Portfolio}$	
$Post_{ct} \cdot PPR_{ic}$	-0.659^{***}	-0.438^{*}	-0.357	-0.651^{***}	-0.973^{***}	-1.078^{***}
	(0.221)	(0.241)	(0.273)	(0.117)	(0.128)	(0.147)
Window	5	7	9	5	7	9
Observations	159,099	122,495	69,055	158,499	121,415	68,365
R^2	0.418	0.420	0.451	0.598	0.599	0.617
Adjusted R^2	0.400	0.401	0.431	0.585	0.586	0.603
Panel B: Patent		$Score_{iat}^{Introduction}$			$Score_{iat}^{Portfolio}$	
$Post_{ct} \cdot PPR_{ic}$	-0.784^{***}	-0.892^{***}	-0.687^{***}	-0.268^{**}	-0.232^{*}	0.048
	(0.173)	(0.175)	(0.185)	(0.130)	(0.132)	(0.131)
Window	5	7	9	5	7	9
Observations	33,046	27,613	19,663	33,034	27,603	19,655
R^2	0.505	0.491	0.485	0.905	0.903	0.914
Adjusted R^2	0.491	0.476	0.469	0.903	0.900	0.912

Note: *p<0.1; **p<0.05; ***p<0.01

Table A.5.3: Stacked Difference-in-Difference—Excluding States and Wider Control Group This table displays results from the estimation of a stacked difference-in-difference, using the sample of firms with trademarks (Panel A) and the sample of firms with patents (Panel B). The dependent variable in columns (1) through (3) are the similarity between startup i's new introduction and the portfolio of a previously close acquirer a ($Score_{iat}^{Introduction}$), and in columns (4) through (6) the dependent variable is the similarity between the startup's portfolio and the portfolio of the previous close potential acquirer ($Score_{iat}^{Portfolio}$). The sample of previously close firms is defined based on the scores after the last introduction. A cohort consists of treated firms located in states where the PPR was implemented and a control group of firms located in a state where adoption of PPR is before the "window". Only firms with at least one introduction in the 3 years leading up to the treatment and at least one introduction in the 4 years following the treatment year are included. All specifications include startup-cohort fixed effects and cohort-year fixed effects, and standard errors clustered at the state level are reported.

Panel A: Trademark	$Score_{iat}^{Introduction}$			$Score_{iat}^{Portfolio}$		
$Post_{ct} \cdot PPR_{ic}$	-0.525^{**}	-0.412^{*}	-0.609^{**}	-0.348^{***}	-0.629^{***}	-0.923^{***}
	(0.205)	(0.221)	(0.260)	(0.109)	(0.118)	(0.139)
Window	5	7	9	5	7	9
Observations	178,999	129,577	71,929	182,086	129,921	71,911
R^2	0.426	0.413	0.442	0.607	0.597	0.614
Adjusted R^2	0.408	0.394	0.422	0.595	0.583	0.600
Panel B: Patent	$Score_{iat}^{Introduction}$			$Score_{iat}^{Portfolio}$		
$Post_{ct} \cdot PPR_{ic}$	-0.784^{***}	-0.892^{***}	-0.687^{***}	-0.268^{**}	-0.232^{*}	0.048
	(0.173)	(0.175)	(0.185)	(0.130)	(0.132)	(0.131)
Window	5	7	9	5	7	9
Observations	33,046	27,613	19,663	33,034	27,603	19,655
R^2	0.505	0.491	0.485	0.905	0.903	0.914
Adjusted R^2	0.491	0.476	0.469	0.903	0.900	0.912

Note: *p<0.1; **p<0.05; ***p<0.01

Table A.5.4: Collapsed Estimation This table displays results from the estimation of a model that corrects for potential serial correlation in the error term (see Bertrand et al., 2004) using the same data as in the original specification presented in table 6. The dependent variable is first regressed on firm-cohort and year-cohort fixed effect. The residuals are then collapsed into one pre-and post-treatment observation, and the effect is estimated only on the treated set of firms. In panel A the cohort-control group includes all firms in states that adopted the policy more than 5 years prior to the treatment, and in panels B and C, the time window is extended to 7 and 9 years, respectively.

	Trademark		Patent	
Panel A: 5 years	$Score_{iat}^{Introduction}$	$Score_{iat}^{Portfolio}$	$Score_{iat}^{Introduction}$	$Score_{iat}^{Portfolio}$
$Post_{ct}$	−0.158	−0.380**	−0.585*	−0.664**
	(0.328)	(0.166)	(0.335)	(0.318)
Observations	808	808	96	96
Panel B: 7 years				
$Post_{ct}$	−0.155	−0.431***	−0.619*	−0.660**
	(0.310)	(0.131)	(0.328)	(0.321)
Observations	808	808	96	96
Panel C: 9 years				
$Post_{ct}$	−0.239	−0.397***	−0.597*	−0.521*
	(0.290)	(0.104)	(0.318)	(0.311)
Observations	808	808	96	96

Note: *p<0.1; **p<0.05; ***p<0.01