Navigating Change in a Dynamic Venture Capital Landscape*

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Abstract:

Entrepreneurial ecosystems evolve continuously as changes in market conditions reshape the opportunities and constraints faced by startups. Yet, how such structural changes affect entrepreneurial activities remains unclear a priori. This paper examines how startups and venture capital (VC) investors respond to shifts in entrepreneurial financing environments by studying the *Seed Boom*, a major transformation of the U.S. VC market between 2009 and 2012, and its implications for startup performance, business strategies, and VC investment practices. Using data on 7,560 U.S. startups founded between 2005 and 2015 and their investors, we characterize the *Seed Boom* as a disproportionate increase in investments in younger startups through smaller financing rounds. Our empirical analysis provides robust evidence that startup performance remained stable in terms of exit outcomes, follow-on equity funding, and the generation of intellectual property. At the same time, startups increasingly differentiate their value propositions, while VCs adapt through greater syndication and staged financing. Consistent with our theoretical arguments, these findings suggest that the organizational structures of startups and VC investors provide substantial adaptive capacity, enabling them to adjust their business strategies as financing environments evolve.

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1 Introduction

Entrepreneurial ventures play a central role in economic growth by generating new business ideas and innovation (e.g., Van Praag and Versloot, 2007; Haltiwanger, 2022). Especially during their early stages, access to sufficient financial resources is essential for startups to realize their growth potential (Hellmann and Puri, 2002; Gimenez-Fernandez *et al.*, 2020; Lerner and Nanda, 2020). The availability of startup financing, however, is continuously reshaped by the broader institutional, regulatory, and technological environment (see Cumming and Li, 2013; Ewens *et al.*, 2018; Denes *et al.*, 2023; Asam and Heller, 2024). For example, following the Global Financial Crisis of 2008, a series of policy initiatives and market-based developments in the U.S. (see Brynjolfsson and Collis, 2019; Edwards and Todtenhaupt, 2020) marked the onset of a fundamental shift in early-stage equity investments between 2009 and 2012. Specifically, venture capital (VC) investors increasingly targeted younger startups through smaller financing rounds – a development that we refer to as the *Seed Boom*.

Such shifts in the entrepreneurial ecosystem reshape established market dynamics and can substantially alter the opportunities and constraints faced by startups. Yet, their consequences for entrepreneurial success remain conceptually unclear. Does a new trend in investment activity simply relax financing constraints for some lower-quality ventures, thereby enhancing the risk of investment misallocation? Or do investors and entrepreneurs adapt to the new financing environment, allowing greater capital availability to sustain startup outcomes? In the context of the *Seed Boom*, anecdotal evidence reflects this conceptual ambiguity: while some practitioners expressed strong skepticism about its implications for market participants, others viewed the development with considerable optimism (see, e.g., The Guardian, 2013; Wall Street Journal, 2014).[1]

In this paper, we investigate this tension by exploring how structural changes in the entrepreneurial ecosystem affect the business activities of startups and investors. In particular, we analyze startups' performance, their founding strategies, and investment patterns throughout the *Seed Boom*. Our sample contains information on the funding activities and firm characteristics of 7,560 U.S.-based startups founded between 2005 and 2015, together with detailed information on their corresponding investors. This setting allows us to examine the impact of a major shift in the entrepreneurial finance landscape on

[1] Critics, such as Sam Altman, argued that abundant capital created false perceptions about the potential of business ideas, with severe consequences ("*mean death*") for most startups. By contrast, proponents, such as Paul Graham, co-founder of Y Combinator, praised the improved access to early-stage financing as a milestone in entrepreneurial finance, arguing that this development "*is the sort of big social shift that only happens once every few generations.*"

the performance and adaptive capacities of startups and investors as key actors within the ecosystem.

We guide our empirical analysis using the resource-based view, which emphasizes that competitive advantage depends on organizations' ability to acquire, combine, and deploy complementary resources effectively (Barney, 1991; Sirmon *et al.*, 2008). Newly emerging ventures often derive their prospective value from pursuing novel business opportunities. To realize this potential and eventually succeed in the marketplace, they must combine their limited internal resources with the complementary financial and managerial support provided by VC investors. However, from a theoretical perspective, it remains unclear whether the *Seed Boom* disrupted or strengthened the formation of such complementary resource bundles. On the one hand, young firms inherently operate under substantial information uncertainty, which may increase the likelihood of investment misallocation. Indeed, particularly during periods of structural change, information frictions complicate investment decisions and the effective allocation of complementary resources by VC investors (e.g., Santamaria and Breschi, 2025). On the other hand, actors in the entrepreneurial ecosystem may possess a high adaptive capacity, which itself constitutes a valuable strategic resource for navigating changing market conditions. For example, pivoting constituting an important strategic response in entrepreneurial ventures (Norbäck *et al.*, 2025), whereas the staged process of VC financing allows investors to respond to changes in market demands (Tian, 2011).

Our empirical analysis sheds light on these perspectives by investigating potential changes in startup performance and organizational practices in the context of the *Seed Boom*. We proceed in three distinct steps. First, we document the *Seed Boom* as a structural shift in the U.S. startup financing environment by describing the public discourse surrounding these market dynamics and quantifying the increase in *Seed* investment activity, its timing, and its potential drivers. Second, we examine startup performance throughout the *Seed Boom* by analyzing startups' IPO and acquisition rates, the ability to secure follow-on financing, and intellectual property generation through patent filings and trademark registrations. We find robust evidence that the *Seed Boom* is not associated with lower performance among *Seed*-backed startups, thereby mitigating concerns that an expansion in early-stage financing necessarily lowers investment quality. This pattern holds across all performance measures and when benchmarking U.S.-*Seed*-backed startups against different comparison groups. Third, we examine whether and how startups and investors adapted their organizational practices during this period. We find that *Seed*-backed startups increasingly differentiated their value propositions from those of their closest competitors. At the same time, VC investors adopted more diversified investment strategies and de-risked their portfolios, for example through greater use of syndication and staged investments. Overall, these findings are consistent with the prevalence of high adaptive capacities within the entrepreneurial ecosystem that help different actors refine their business strategies under dynamic market conditions.

Taken together, our findings offer new perspectives on the entrepreneurship literature by focusing on startup performance and adaptation processes in dynamic entrepreneurial ecosystems. We document a significant yet understudied transformation of the U.S. startup financing landscape toward *Seed* investments. Beyond characterizing these trends, our analyses suggest that startups sustained their performance under changing financing conditions while adapting their business strategies, whereas VC investors simultaneously adjusted their investment practices. This co-adaptation between entrepreneurial ventures and their investors highlights how actors in entrepreneurial ecosystems respond to structural change, offering a dynamic perspective on the entrepreneurial process.

With these insights, our paper contributes to the literature in several ways. As the core dimension, it contributes to research on entrepreneurial management and business venturing by examining competing perspectives on the potential impact of structural changes in the entrepreneurial ecosystem. Prior research recognizes that sustained startup performance depends on complementarities between startup resources and investor capabilities (Dushnitsky and Lavie, 2010; Alvarez-Garrido and Dushnitsky, 2016; Santamaria and Breschi, 2025), and that these complementarities may shift as regulatory, technological, and broader market conditions evolve (Lungeanu and Zajac, 2016; Barney *et al.*, 2021; Abuzov, 2024). However, whether such complementary resource bundles can be maintained as financing environments change remains largely unexplored. Our findings inform this debate by suggesting that startups can sustain their performance under changing financing conditions. Importantly, this pattern coincides with both entrepreneurial ventures and VC investors adapting their organizational practices. From a conceptual perspective, our findings thus emphasize the idea that adaptive capacity is itself a value-relevant resources through which resource complementarities are maintained in dynamic markets.

Furthermore, our analysis extends research in entrepreneurship that investigates the performance effects of VC investments (e.g., Hellmann and Puri, 2000; Puri and Zarutskie, 2012; Alperovych and Hübner, 2013; Norbäck *et al.*, 2025) by showing that the value created by investors is not tied to a stable financing environment. Instead, our findings suggest that investors continue to create value by adapting both their investment strategies as the financing needs of entrepreneurial ventures evolve. This perspective shifts attention from the resources possessed by investors toward their capacity to continuously reconfigure these resources alongside the startups they finance.

Finally, our analysis offers new insights into the entrepreneurial finance literature examining how institutional and market developments shape startup financing and entrepreneurial outcomes (Cumming and Li, 2013; Ewens *et al.*, 2018; Edwards and Todtenhaupt, 2020; Asam and Heller, 2024). We extend this literature by focusing on the rise of early-stage *Seed* investing and its implications for startup performance in a rapidly evolving VC market. Using a novel and highly relevant empirical setting, our findings highlight that structural changes in entrepreneurial finance are accompanied by mutual adaptations of startups and investors, thereby underscoring the dynamic nature of entrepreneurial financing ecosystems.

2 Theoretical considerations

In this section, we develop a conceptual perspective on the potential implications of the *Seed Boom* for startup and investor activities. To this end, we draw on management and entrepreneurship theory to examine how changes in the entrepreneurial financing environment may affect startup performance and the organizational responses of startups and VC investors.

Resource availability and entrepreneurial activities: Entrepreneurial activities involve the recombination of available resources to overcome the limitations of existing solutions (e.g., Baker and Nelson, 2005). According to Barney (1991), all imperfectly imitable and non-substitutable tangible and intangible assets controlled by a firm constitute value-relevant resources. Access to such resources is essential for entrepreneurial firms to develop competitive advantages (Alvarez and Barney, 2001). However, entrepreneurial ventures face pronounced liabilities of newness and smallness, which constrain their ability to generate or acquire these resources and may ultimately slow their development (Gimenez-Fernandez *et al.*, 2020). Most startups generate little, if any, operating cash flow during their early stages, making internal financing and bootstrapping insufficient to sustain anticipated growth trajectories (see Hellmann and Puri, 2002; Block *et al.*, 2018; Lerner and Nanda, 2020). Further, startups often face constraints that extend beyond financial capital to include limited operational experience, strategic capabilities, and industry-specific networks (e.g., Brinckmann *et al.*, 2011; Nahata, 2019).[2] These factors are most binding during the earliest stages of a startup's life cycle (Ko and McKelvie, 2018), making young ventures particularly dependent on complementary resources provided by other actors in the entrepreneurial ecosystem (e.g., Kor and Mahoney, 2005; Santamaria and Breschi, 2025).

As a central actor in this ecosystem, VC investors provide critical financial and organizational resources to nascent, resource-constrained ventures. They act as specialized financial intermediaries that acquire equity stakes while simultaneously supplying financial capital and organizational support. Beyond providing financial capital, VC investors actively monitor, govern, and advise their portfolio companies (Casamatta, 2003; Bottazzi *et al.*, 2008; Bernstein *et al.*, 2016). Through these activities, VC investors provide startups with access to complementary organizational resources and capabilities, which support startup growth and eventually help ventures overcome the liabilities of newness and smallness (Kaplan *et al.*, 2009). From a conceptual perspective, these aspects suggest that VC investors can enable startups to combine internal and external resources into unique resource bundles that can generate sustained competitive advantages.

However, realizing these complementarities requires VC investors to accurately evaluate entrepreneurial opportunities based on the signals available to them (Haeussler *et al.*, 2014; Colombo, 2021). As such, inadequate screening increases the risk of investment misallocation (Abuzov, 2024). This aspect is important in the context of dynamic market environments, as they may exacerbate information asymmetries (Bylund and McCaffrey, 2017) and, thus, make it more difficult for investors to effectively assess potential investment targets. Conceptually, such information asymmetries make it harder for VCs to identify the right complementarities.

Together, these considerations form the foundation for evaluating how structural changes in the entrepreneurial financing environment may influence startup and investor behavior. The effects of such periods of change are likely to depend on whether they alleviate resource constraints or exacerbate information frictions. Against this background, we derive several predictions about how the *Seed Boom* may have affected the business activities of startups and investors.

Dynamic markets and startup performance: As a first dimension, we turn to startup performance. From a resource-based perspective, a shift in startup financing toward younger ventures may weaken

[2] Our analysis abstracts from the complementary role of human capital and instead focuses on the performance implications of financial development in the startup ecosystem.

the formation of complementary resource bundles and thereby reduce startups' probability of success. Rapidly changing market conditions may impair VC investors' effectiveness to both identify promising investment opportunities and provide adequate resources to target startups. Investment decisions are necessarily based on noisy signals, including characteristics of the founding team and the firm's business model (Gompers *et al.*, 2020; Colombo, 2021). These challenges are likely more binding in dynamic markets, i.e., when attention constraints are high (Abuzov, 2024). For example, prior literature shows that such environments may induce VCs to pursue a "*spray and pray*" investment strategy, in which they provide small funding amounts and limited governance to a larger number of startups (see Ewens *et al.*, 2018). From a theoretical perspective, a spray-and-pray approach reduces the ability of VCs to provide complementary managerial resources to startups. Additionally, investments into early-stage ventures may also be less effective under changing market conditions. Indeed, periods of change imply that the non-monetary needs of startups adjust and, hence, it becomes more difficult for VCs to provide the financial, managerial, and organizational support required under changing market conditions. These arguments suggest that the *Seed Boom* may have weakened VC investors' ability to identify promising startups and assemble the complementary resource bundles required for their success.

Notwithstanding, theory also allows for alternative perspectives, suggesting that funding shifts toward younger investment targets do not lead to investment misallocation. From an entrepreneurial finance perspective, early-stage investments resemble real options rather than conventional capital budgeting projects (see Berk *et al.*, 2004). With a small initial investment, VCs obtain the option to provide additional financing over time, i.e., after uncertainty is (partially) resolved. Providing follow-on financing is optional rather than obligatory, allowing investors to respond to information revealed over time. Staged financing therefore constitutes a mechanism for experimentation that enables investors to terminate poor projects while scaling successful ones over time (Tian, 2011; Alimov and Hertzel, 2024). This is particularly worthwhile in cases in which firms possess a high degree of strategic flexibility, such as small growth-oriented ventures. Accordingly, a shift towards funding younger firms may reflect rational option-based investing rather than capital being diverted toward inferior targets. Conceptually, staged financing enables investors to adapt complementary resource provision over time.

Taken together, these competing perspectives show that transition periods in the entrepreneurial financing environment, such as the *Seed Boom*, create two opposing forces regarding the performance implications for startup. On the one hand, heightened information asymmetries may increase the risk of investment misallocation by making entrepreneurial opportunities more difficult to evaluate. On the other hand, easing financing constraints allows startups to access critical complementary resources at an early stage. Hence, investigating whether the expansion of early-stage financing increased investment misallocation or reflected adaptive investment behavior remains an empirical question, which we address in our empirical analysis.

Adaptive capacities in the entrepreneurial ecosystem: Although the preceding discussion yields competing predictions regarding startup performance, both perspectives imply that structural change may induce adaptive responses by both startups and investors. From a resource-based perspective, adaptive capacity itself can be viewed as a valuable organizational capability that enables firms to reconfigure resources in response to changing market conditions (e.g., Barney *et al.*, 2021). Compared to more mature firms, young startups are found to be more flexible in adapting to changing market environments (Kerr *et al.*, 2014a). Especially during the earliest stages of a firm, experimentation plays a central role in generating viable business ideas, which can convince (prospective) stakeholders about the startup's potential (Zahra, 2021; Koning *et al.*, 2022). Greater availability of early-stage financing extends startups' experimentation horizon, allowing entrepreneurial teams to refine, revise, and pivot their business models before financial constraints become binding. This reasoning is consistent with the resource-based view, according to which organizations recognize business opportunities based on resource availability (Barney, 1991; Barney *et al.*, 2001). Therefore, an increase in early-stage funding gives more startups the opportunity to overcome their liabilities of newness and smallness by allowing them to exploit the flexibility of their organizational structure. Accordingly, the *Seed Boom* may have encouraged greater experimentation and a broader variety of founding strategies among newly established ventures.

In addition to startups, also other market participants can be expected to exhibit high degrees of adaptive activity. In particular, the business model of VCs is well-suited to adapting to changes in the market environment. Their staged investment model allows them to continuously update investment decisions and adjust the timing and magnitude of resource commitments as uncertainty is resolved (Gompers, 1995; Tian, 2011). Such flexibility allows VCs to adjust both their investment strategies and the complementary financial and managerial resources they provide as market conditions evolve.

These arguments suggest that periods of structural change reveal the adaptive capacities of both startups and investors. Rather than passively responding to changing financing conditions, both groups may actively adjust their organizational practices in ways that preserve complementary resource bundles. Examining whether such adaptations emerged during the *Seed Boom* is therefore an empirical question, which we address in the following analysis.

3 Data and the institutional setting

3.1 Classifying early-stage investments

Our empirical analysis requires a specific and time-consistent classification of startup investment deals. Distinct thresholds will allow us to effectively capture changes in investment patterns and startup performance in a dynamic market environment, rather than, for instance, merely reflecting differences in labeling practices over time. However, there are no universally applicable thresholds in investment characteristics that delineate early-stage external equity investment categories, such as Pre-seed, Seed, or Series A deals. In particular, databases commonly employed in the entrepreneurship or innovation literature tend to use overlapping definitions regarding investor profiles, startup lifecycle stages, and investment sums.[3]

For these reasons, we define distinct thresholds to classify *Seed* rounds, focusing on two main characteristics: investment volumes and target age. These characteristics refer to the most basic features of *Seed* investments, as they occur at very early stages of the startup lifecycle and involve relatively small deal volumes. As an objective threshold, we consider the median investment volume and target age of first-round equity deals in the U.S. during 2005 and 2006 (i.e., our first sample years). Hence, we collectively refer to *Seed* rounds as all first-round equity investments with a maximum deal volume of two million USD targeted at firms within the first two years after incorporation. By applying this definition, we do not seek to improve existing classifications but rather aim to have a consistent definition that allows us to assess changes in investment patterns in terms of deal size and target age over time.[4]

Moreover, we consider only startups backed by VC investors. This focus is advantageous as it rules

[3] For example, Crunchbase distinguishes: 1) Pre-seed and angel rounds refer to small deals below 150,000 USD that typically do not involve VC companies. 2) Seed rounds commonly range between 0.1 and 2 million USD, with target firms usually in their first years after incorporation, and investors often being VCs. 3) Early-stage VC rounds (Series A and B) typically range between 1 and 30 million USD and, just like *Seed* deals, targets are still seeking product/market fit; however, targets can be more established firms, usually involving larger deal sizes of at least 10 million USD.

[4] Most investments that are classified as *Seed* deals according to this definition are also labeled as Seed investments in Crunchbase (see Table IA1, Appendix). Still, in robustness tests, we show that adjusting these thresholds or using the Crunchbase label does not qualitatively change our main findings.

out some confounding factors that arise from differences in investment strategies specific to other early-stage equity investors, such as angel investors or incubators (e.g., Block *et al.*, 2019; Do *et al.*, 2026). In fact, VCs are the most professional and reputable types of investors in early-stage startups, with the mandate to select and actively manage a portfolio of innovation-intensive startups to maximize returns on behalf of their capital providers (Hellmann and Puri, 2002; Bottazzi *et al.*, 2008).

3.2 Data and summary statistics

Data on startups and their investors come from Crunchbase and contain all basic information on the respective firms, individual funding rounds, and founder characteristics. We complement the data with information about startups' patenting and trademark filings from the USPTO Patent Examination Research Dataset (PatEx), the Trademark Case Files Dataset, and the worldwide patent statistical database PATSTAT. The initial sample covers all startups with a registered address in the U.S. that received a first-round equity investment from a VC investor between 2005 and 2015. Selecting 2015 avoids truncation issues in the performance outcomes. We follow related literature and exclude firms incorporated more than five years before their first recorded deal (e.g., Edwards and Todtenhaupt, 2020). We classify the remaining firms into initially *Seed*-backed and other startups and select those backed by VCs as outlined in Section 3.1. We distinguish professional VCs from other investors using the Crunchbase labels "organizations" (mnemonic `organization_type`), i.e., investors whose type labels include "venture capitalist" or "micro VC" (mnemonic `investor_type`). The final startup-level sample contains information on 4,894 *Seed*-backed startups and 2,666 other VC-backed startups that did not receive *Seed* financing.

Our analysis considers three distinct dimensions of startup performance. First, we assess whether startups successfully exit, i.e., by having an initial public offering (IPO) or being acquired. Second, we use data on the total equity investment volumes secured by startups over time. Funding volumes are well-suited alternative performance indicators, especially when sample startups are too young for an acquisition or IPO, such as in our case (Yimfor and Garfinkel, 2023). Third, we consider the creation of intellectual property (IP) rights, such as patents or trademarks, as a performance dimension. Examining IP filings as a further performance indicator for startups aligns with the observation that early-stage equity financing is particularly relevant for young innovative startups (e.g., Cockburn and MacGarvie, 2009; Howell *et al.*, 2020). To account for potential truncation issues, we measure all performance outcomes eight years after incorporation. Table IA2 (Appendix) lists all variables used in the analyses.

Table 1 provides summary statistics on sample startups. By definition, they are very small and young at the time of the initial investment, with an average age of less than one year (0.79 years). Likewise, the average deal size is relatively small (0.95 million USD). More than one out of five of the *Seed*-backed startups is eventually acquired (22.5%), but only very few of them are acquired in a large deal of at least 100 million USD (1.4%) or exit via IPO (0.7%). With a median number of two investment rounds, most startups are able to secure follow-on funding (66%). Overall, about 28% of startups file either for a patent or register a trademark. Intuitively, sample startups are predominantly located in states known for their strong entrepreneurial ecosystems, such as California, New York, and Massachusetts (see Figure IA1, Appendix). In terms of sectoral distribution, *Seed*-backed startups are generally more likely to operate in low captial intensive sectors, such as software, internet services, or data analytics (see Table IA3, Appendix).

- Insert Table 1 here -

In addition to the startup-level dataset, we construct a complementary investor-year panel. It covers 7,314 VC investors that made a first-round investment between 2005 and 2015 into any of the sample startups. We calculate their total number of investments for each year in the respective time window and add investor-level controls from Crunchbase. Table IA4 (Appendix) displays some basic characteristics of this data. About half of *Seed* investments are syndicated deals involving more than one investor (54%), and they involve investors located in the same state (52%). The share of corporate venture capitalists (CVCs) among the first-round investors in our sample is relatively small (7%).[5] Further, the statistics emphasize that investors select startups based on the available quality signals, which evolve as startups mature. For example, the founding teams of *Seed*-backed targets more frequently have prior experience in launching and exiting a startup (28% and 6%) compared to founders of other startups (16% and 4%), despite their relatively similar founder ages. Moreover, *Seed*-backed startups own fewer tangible outputs, such as patents (9%), before the initial investment round, compared to other early-stage equity-backed startups (33%). These patterns confirm prior literature on the VC decision-making process, showing that investors initially focus on the founding team characteristics as long as startups have no track record of operational performance and move to more tangible criteria later on (e.g., Gompers *et al.*, 2020).

[5] *Seed* investors are younger than non-*Seed* investors, with an average age of about 8 versus 13 years. Still, the two investor types have very similar levels of experience, as measured by their average Crunchbase "rank" (mnemonic `rank`). The variable resembles investors age-adjusted number of connections linked to their Crunchbase profile.

3.3 The rise in early-stage startup financing in the US: The *Seed Boom*

Anecdotal evidence: There is ample annecdotal evidence that the U.S. entrepreneurial finance landscape experienced a period of subtantial changes following the Global Financial Crisis in 2008. For example, Josh Kopelman, a partner at *First Round Capital* and an early-stage venture capitalist, claims that it has become much easier and faster for an entrepreneur to raise a first round in the early 2010s than ever before (Kopelman, 2015). With this, he described a specific development, in which first-round VC investment targets become increasingly younger, with deal sizes declining accordingly. Other business insiders reinforce this observation, such as Peter Wagner, a leading tech investor at *Wing Venture Capital*. He reports that *Seed* deals gained a new role during the early 2010s, serving as a primary mode of first-round equity investment (Wagner, 2021).

At the time, the public discourse about the potential impact of the rise in *Seed* funding for startup performance came to quite divergent conclusions, reflecting the opposing views on the potential performance implications discussed in Section 2. The common argument of skeptics was that easy-to-receive first-round funding would create a misleading perception about the potential of respective ventures. With more startups obtaining small-sized first-round deals, the chances for the average startup to secure follow-on funding may have decreased due to higher competition – a situation which Kopelman (2015) refers to as "*Series A Crunch*". The popular press and prominent investors backed this view (e.g., Wall Street Journal, 2014). For example, Sam Altman posted on Twitter in 2014 that "*seed money is so easy to raise [...] that founders assume they can just raise more money whenever they want. [T]his meets cold reality when companies try to raise money again, mean[ing] death*" for most startups.

By contrast, other practitioners praised the improved access to early-stage financing as a milestone in startup finance with the ability to unleash entrepreneurial potential on a large scale (e.g., The Guardian, 2013). The underlying policy- and market-based changes were thought to facilitate access to value-relevant resources, eventually supporting the emergence of new business models. To illustrate, Paul Graham, founding CEO of Y Combinator, stated in 2013: "*When I graduated from college in 1986, there were essentially two options: get a job or go to grad school. Now there's a third: start your own company.*" Such a change "*is the sort of big social shift that only happens once every few generations.*"

Descriptive evidence: Against this background, we use our sample data to document the basic patterns of the changes in the early-stage VC investments at the time. The numbers in Table 2 show a rapid increase in the number of first-round VC investments between 2005 and 2015, with the highest year-over-year growth rates of about 50% in 2010 and 2011. By definition, between 2005 and the end of the Great Financial Crisis in 2009, the share of *Seed*-backed and other startups among total investments was fairly balanced. Between 2009 and 2012, however, the number of *Seed* rounds surged about fourfold. This increase was disproportionate compared with those in other VC rates, which grew by a factor of 1.7 during the same period. Likewise, the sharp rise in *Seed* rounds notably exceeds the rate of startup creation in the U.S. at the time (Column "*Startup creation*" in Table 2). In sum, these figures closely align with the observations of practitioners about the rise in *Seed* deal described above.

- Insert Table 2 here -

To mitigate concerns that these patterns stem from specific features in the Crunchbase data, Figure IA2 (Appendix) displays different variants of measuring the prevalence of *Seed*-backed startups. As a benchmark, Panel A compares the evolution of startups receiving initially *Seed* or other VC equity financing over time using the original *Seed* definition as introduced in Section 3.1. We then show that this pattern does not qualitatively change when using Crunchbase labels (Panel B), Pitchbook classifications of seed investments (Panel C), when restricting the sample to startups whose investors are solely labeled as "venture capitalist" or "micro VC" (Panel D), when singling out CVCs (Panel E), and when comparing the *Seed Boom* with underlying developments of business formations in the U.S. (Panel F).

Timing of the *Seed Boom*: Next, we examine the specific timing of the observed shift. To this end, we deploy multivariate analyses on the rate of *Seed* investments during our sample period using the investor-year panel introduced in Section 3.2. The regressions use the number of *Seed* deals as a share of total investments closed by respective investors as the dependent variable and control for investor fixed effects and investor experience (measured both in terms of investment rounds and age), investor locations, and their Crunchbase rank score. The main regressors is Post^{Υ}, which equals one for each year $\Upsilon \in [2008, 2012]$, and zero otherwise. Standard errors are clustered at the investor level.

Table 3 displays the coefficients of Post^{Υ}. For the years 2008 and 2012, the corresponding coefficients are small and statistically not significant, whereas for the years 2009, 2010, and 2011, the respective coefficients are highly significant and much larger, with the effect size being largest for the years 2010 and 2011 (0.150 and 0.122). The coefficients are also economically meaningful, suggesting an increase in the average number of *Seed* deals by 18 to 14% per year relative to their pre-2009 share of 0.854. These patterns also hold when using a continuous count measure of *Seed* investments, the Crunchbase definition of *Seed*-backed startups, and event study type regressions (see Table IA5, Appendix). Importantly, they do not apply to other first-round VC deals.[6]

- Insert Table 3 here -

To further verify these patterns, Figure 1 plots the distributions of target firms' age and deal volumes of respective first-round equity deals. Consistent with the numbers displayed in Tables 2 and 3, the graphs show a significant shift in respective distributions toward younger target firms and smaller deal sizes. When comparing the three stages of the *Seed Boom* (i.e., before, within, and afterward), the graph illustrates a *gradual* shift along both dimensions.

- Insert Figure 1 here -

Overall, these analyses consistently document the disproportionate increase in first-round *Seed* investments in the U.S. during the period 2009 and 2012. This *Seed Boom* exceeds that of other early-stage investment types and startup creation rates and confirms anecdotal evidence at the time. While 2010 marks the pivotal year of this trend, we conjecture that this development can be best described as a rapid but still gradual rise of *Seed*-backed startups over the course of two to three years. We operationalize the *Seed Boom* in the empirical section, accordingly.

Factors contributing to the *Seed Boom*: Such economy-wide transformations, such as the *Seed Boom*, rarely have a singular cause, but instead often emerge from complex combinations of multiple underlying factors (e.g., Hidalgo, 2023). In line with this idea, we take on two complementary perspectives by focusing on policy- and market-based developments as potential determinants of the rise in *Seed* investments.[7] As a common feature, both factors significantly impacted the overall conditions for startup financing by modifying the underlying market structure.

First, policy-based factors are a crucial dimension that likely fostered the rise of *Seed* investments. Governments worldwide commonly deploy a wide range of tools to support startup financing (see Cum-

[6]The regressions in Tables 3 and IA5 include firm fixed-effects and, thus, the results indicate that existing investors increasily switched toward *Seed* rounds (i.e., intensive margin). Repeating these estimations without fixed effects yields qualitatively similar estimates (undisplayed). These results suggest that the *Seed Boom* was driven by both existing investors switching to *Seed* deals as well as newly entering investors (i.e., extensive margin).

[7]Providing an exhaustive assessment on the question about the relative importance of the different factors for triggering the *Seed Boom* goes beyond the scope of our analysis. We acknowledge that other factors may also affect the prevalence of *Seed* investments at the time.

ming and Li, 2013; Denes *et al.*, 2023). In the following, we consider the *Small Business Jobs Act* (SBJA) as one specific policy that was adopted at the onset of the U.S. *Seed Boom*. The SBJA was a key policy change that incentivized investments into early-stage startups by providing potential investors with a tax exemption on realized profits. Its implementation allowed investors a full exemption from federal taxation of capital gains realized after September 27, 2010, on the sale of the shares of certain entrepreneurial startups, with eligibility depending on the actual business scope of the startup. It is well-documented that the law made VC investments in these qualified startups significantly more attractive (see Edwards and Todtenhaupt, 2020).

We illustrate that the SBJA can be associated with the *Seed Boom* by analyzing differential trends among startups in sectors eligible for SBJA tax exemption and those that are not. Panel A of Figure 2 shows that eligible startups account for most of *Seed* deals between 2009 and 2012, but not before. This pattern does not apply to relatively larger first-round equity investments and, thus, does not reflect a general trend of increased investments into SBJA-eligible sectors (see Figure IA3, Appendix). These patterns are consistent with the idea that specific policy-based factors contributed to the rise in *Seed* financing during the early 2010s. At the same time, they also emphasize that other contributing factors were at play. As such, the tax exemptions stipulated by the SBJA were only initiated in late 2010, whereas our previous analysis document that the rise in *Seed* investments already emerged as of 2009.

- Insert Figure 2 here -

In this light, we consider a second factor that was likely important for explaining the *Seed Boom*. Specifically, we conjecture that the emergence of low-capital-intensive startups marked a critical, market-based factor contributing to the increase in *Seed* investments. Since the early 2000s, the US economy has been increasingly moving toward a more digital marketplace (e.g., Brynjolfsson and Collis, 2019). Digital business strategies rely more on intangible assets that require less upfront capital investment. Consistently, advancements in the tech industries lowered the amount (and timing) of funding needed to start a business throughout the 2000s (see Ewens *et al.*, 2018). Fueling this trend, the post-crisis years presented an attractive financing environment due to fairly cheap money available for startup financing (see Lerner and Nanda, 2020) and the launch of various financing platforms that facilitated early-stage financing activities (Cohen *et al.*, 2019). These factors likely accelerated the inflow of *Seed* investments, especially into less capital-intensive startups.

To operationalize the capital intensity of sectors, we use business field classifications of the so-called FAANG companies, i.e., a group of five Big Tech companies at the time, namely, Facebook, Amazon, Apple, Netflix, and Google. The Financial Times (2020) coined the 2010s as "*The FAANG Decade*", referring to the disproportionate growth of the tech sector in the 2010s. We define low-capital-intensive startups as those operating in the same business fields as these FAANG companies (i.e., software, data, internet, cloud, platforms, apps, security, and payment), as listed in Table IA6 (Appendix).

Similar to before, we test the relationship between capital intensity and the *Seed Boom* by examining the sectoral composition of startups that account for the rise of *Seed* investments. Panel B of Figure 2 shows that the relative incidence of *Seed* deals across high- and low-capital-intensive sectors is comparable until 2009. Afterward, low-capital-intensive startups disproportionally attract more *Seed* deals. Again, this pattern does not apply to larger first-round equity investments and does not reflect a general trend of increasing investments into low-capital-intensive sectors (Panel B of Figure IA3, Appendix).

Taken together, these statistics illustrate that specific policy- and market-based factors likely have contributed to the rise of *Seed* investments in the aftermath of the Great Financial Crisis. In fact, when considering the intersection of startups that are subject to both factors, we find that the observed patterns are predominantly driven by these startups (see Figure IA4, Appendix). This insight further highlights the complementary importance of different underlying factors to spur economy-wide transformations, such as the *Seed Boom*.[8]

4 Implications of the *Seed Boom*

4.1 Startup performance and the *Seed Boom*

Descriptive analysis: We proceed by assessing the performance patterns of *Seed*-backed startups throughout the *Seed Boom*. As a starting point, we evaluate the probability that a startup reaches a performance milestone over time, using Kaplan-Meier failure estimates ("hazard rates"). To do so, we reshape the main sample to a startup-month panel in which startup age is measured in months relative to the incorporation date. Successful performance events are indicated using dummy variables that are equal to one in the month the startup reaches a given performance event for the first time, and zero

[8]This additional insight is also important in confirming that the *Seed Boom* marks an unanticipated event, as suggested in the previous analyses, i.e., Panel C of Table IA5 (Appendix). For instance, given that the policy- and market-based factors were unanticipated themselves (see Lerner and Nanda, 2020; Edwards and Todtenhaupt, 2020), their joint implications could hardly be anticipated by market participants.

otherwise. Specifically, we compare the hazard rates before and after the *Seed Boom*, requiring us to choose a specific threshold to delineate the two periods. For simplicity, we first chose the year 2010 for a before-and-after comparison, which aligns with the statistics of the *Seed Boom* from Section 3.3.

Figure 3 shows that the probability of *Seed*-backed startups to successfully exit does not significantly change comparing pre- and post-2010 levels. For example, the probability to exit via an acquisition within the first six years after incorporation changed from 18% before 2010 to 20% afterwards. This difference is statistically insignificant, as shown by the overlapping confidence intervals of the hazard rates. These patterns are very similar for large acquisitions with at least 100 million USD and IPO rates (see Panel A).[9] More generally, these results also apply for other funding outcomes such as the likelihood of *Seed*-backed startups to obtain follow-on funding (Panel B). For example, the probability of obtaining any follow-on funding moderately decreases from about 69% before 2010 to 63% thereafter, but this difference is statistically insignificant.[10]

- Insert Figure 3 here -

Several tests show that these patterns do not hinge on the specific estimation approach. More specifically, the observations are not contingent on choosing 2010 as a cutoff (Panel A of Figure IA6, Appendix), they also hold in a multivariate setting (Table IA8, Appendix) and when considering liquidation rates of *Seed*-backed startups after incorporation (Panel B of Figure IA6).[11] Overall, the descriptive assessment provides a consistent picture across a variety of performance outcomes, suggesting that the *Seed Boom* is unlikely to be associated with a decline in startup performance. These patterns are unlikely to suffer from reverse causality (i.e., performance outcomes are measured several years after the initial investment) or measurement errors due to the large number of performance measures and estimation approaches. Nevertheless, endogeneity presents a particular challenge when studying early-stage ventures, for instance, due to data limitations. In our analysis, endogeneity arising from omitted variables

[9] In both cases, the probability of occurrence is fairly low. For example, the probability of an IPO in the overall sample is less than 1%. For complementary statistics on acquisition and IPO rates, see Table IA7 (Appendix).

[10] We also assess startups' IP filings over time. This performance measure may be less informative in a univariate setup, given that IP activity is sector-specific and the *Seed Boom* entails a compositional shift in business fields toward less IP-intensive, low-capital-intensive fields. Consistently, the probability of a *Seed*-backed startup to file patents or trademarks within the first six years after incorporation is significantly lower after 2010 than before (see Figure IA5, Appendix).

[11] Liquidation rates are a useful alternative indicator of startup performance (i.e., failure) because liquidation often implies that investors write off their entire investment. Arguably, failure rates are prone to being underreported in observational data, which is why we refrain from using them throughout the analysis. However, since the hazard estimations are a within-sample analysis, we can compare reported liquidation rates of *Seed*-backed startups before and after 2010, assuming that the *Seed Boom* did not affect the reporting patterns of liquidations. Overall, 27% of startups in the sample are liquidated by the end of 2023, i.e., the latest available update of our sample data. This figure is in line with statistics on liquidation rates of VC-backed startups in the U.S. for the years between 2000 and 2010 (see Wall Street Journal, 2012).

is an apparent concern, since the previous findings likely do not fully account for other contemporaneous events or covariates that simultaneously influence startup performance.

Matched sample regressions: Next, we deploy matched sample regressions, comparing the performance of *Seed*-backed startups throughout the *Seed Boom* with that of very similar startups that did not receive *Seed* investments but other external equity investments at an early stage. In doing so, we seek to to move one step further in addressing concerns about pre-existing differences in common determinants of startup performance that may drive the observed performance patterns. Our matching approach does not provide us with two identical groups of firms from which one set is randomly treated (in the sense of treatment and control groups) and, therefore, our claim is not that we eliminate endogeneity issues altogether. Instead, our objective is to obtain two sets of VC-backed firms that are comparable at the time of incorporation and, thereby, significantly mitigate these concerns by accounting for the most important observable differences across firms.

To create the matched sample, we use a combination of exact matching and Coarsened Exact Matching (CEM). *Seed*-backed and matched startups must share the same incorporation month, location (state), and business field. Moreover, we impose that startups in the comparison group have obtained a first external equity investment but no *Seed* investment. Specifically, following the definition in Section 3.1, startups in the comparison group secured an initial equity deal two years after incorporation or later at a minimum of two million USD. As continuous matching parameters, we consider previous founding activities and founder age to account for the experience of startups' founders at incorporation. CEM then assigns firms with similar characteristics into distinct strata. We allow for multiple firms within one stratum but remove observations that without a matching partner. This final matched sample comprises 2,041 startups, out of which 1,148 are initially *Seed*-backed startups. As a validation test, we compare the performance of the two comparison groups by initial funding year-cohorts in order to assess differences in their pre-*Seed Boom* performance. We find no substantial differences in respective patterns between *Seed*-backed and comparison group startups for the 2005-2010 cohorts (see Figure IA7, Appendix).

We formally estimate the relationship between the *Seed Boom* and startup performance using the following fixed effects probit estimation specification:

$$I(P_i) = \beta(SeedBoom_t \times Seed_i) + \gamma X_{it} + \beta_\tau + \beta_j + \varepsilon_{it} \quad , \tag{1}$$

where $I(P_i)$ are different dummy variables indicating whether the startup i that belongs to the funding-year cohort t has reached a given performance outcome within eight years after incorporation. As before, performance outcomes are successful exits, the probability of follow-on funding, funding targets, and filings of IP rights. The variable $SeedBoom_t$ measures the different phases of the *Seed Boom*. In our preferred specification, we use the ratio of *Seed*-backed funding deals among early stage-equity investments in the U.S., as displayed in Table 2. For robustness, we also use a dummy that is equal to one if a startup receives funding after 2010, and zero otherwise. In both cases, the coefficient of interest, β, captures the probability of *Seed*-backed startups to reach a given performance goal (P_i), comparing startups founded at different stages of the *Seed Boom*. Industry fixed effects (β_j) control for structural, time-invariant differences in firm performance across business fields. Incorporation-year fixed effects (β_τ) capture age differences at the initial investment event. Further, X_{it} is a vector of time-variant controls, including founder characteristics of location dummies for startups incorporated in California or New York. Standard errors are clustered at the startup level.

Regression results: Table 4 displays the regression results reporting the relationship between startup performance and the *Seed Boom*. Across specifications, the coefficients of the interaction term $SeedBoom \times Seed$ are insignificant. These results apply when using both the continuous measure of the *Seed Boom* (Panel A) as well as the binary $Post^{2010}$-indicator (Panel B). Further, these estimates are not sensitive to using 2009 or 2011 to delineate pre- and post-*Seed Boom* periods or using the *Seed* investments definition of Crunchbase to classify startups (see Table IA9, Appendix). Notably, most of the coefficients on the interaction terms of any of the previous matched-sample regressions are insignificant but also negative. To mitigate potential concerns in this regard, we show that the results apply when considering all startups eligible for the SBJA tax exemption and those active in low-capital-intensive sectors. The underlying idea is that startups in these sectors account for the majority of the *Seed Boom* and, thus, a potential performance decline should be most salient here. Still, we also do not find statistically significantly negative results for particularly exposed startups (see Panels D–F of Table IA9).

- Insert Table 4 here -

Furthermore, we conduct another robustness test, mitigating concerns about the definition of the comparison groups. The previous analyses compare startups that initially receive different types of external equity funding, which is likely endogenous to startup characteristics and, thus, may be informative about performance outcomes in itself. To address these concerns, we analyze *Seed*-backed startups subject to the *Seed Boom* and other *Seed*-backed startups that operate in an environment where the effects of the shift in the entrepreneurial finance landscape were absent. In particular, we compare U.S.-based *Seed*-backed startups with other *Seed*-backed startups from six OECD economies with large VC markets that are broadly comparable to the U.S. VC market but did not experience a surge in *Seed* investments between 2009 and 2012: Israel, Great Britain, Germany, France, Sweden, and the Netherlands.[12] We obtain the sample of non-U.S.-based startups by applying the same selection criteria as in Section 3.1 for startups incorporated in any of these countries. To formally examine performance differences between these subgroups, we estimate regressions that are similar to Equation (1) but replace the *Seed*-dummy with $Seed^{US}$, which equals one for all *Seed*-backed startups incorporated in the U.S., and zero for startups incorporated in any of the six countries listed above.[13] As before, our claim is not that this approach yields identical treated and control groups, but it helps addressing concerns about omitted variables (i.e., the endogenous selection into the treatment group) that may explain performance differences.

Table IA10 (Appendix) displays the corresponding estimates comparing the performance of U.S. and non-U.S.-based startups. As before, these results show that the *Seed Boom* is unlikely to be associated with a negative impact on startup performance (see Panels A and B). There is no statistically significant differential effect regarding startups' probability of having a successful exit throughout the U.S. *Seed Boom* (Columns I-IV). While we find moderate negative estimates for the funding-related performance indicators (Columns V-IX), this effect vanishes when using only startups that are active in low-capital-intensive sectors eligible for the SBJA tax exemption (see Panel C). Overall, the results are consistent with the descriptive evidence presented before, suggesting that there are no significantly negative implications of the *Seed Boom* for startup performance.

4.2 Adaptive capacity of startups and VC investors

In the absence of significant changes in overall startup performance, the discussions in Section 2 suggest that dynamic market conditions instead evoke market participants to adapt their business strategies. To

[12] These economies have fairly similar VC markets compared to the U.S. in terms of their VC sector size (see OECD Statistical Warehouse, 2010). We do not consider China and Japan despite having sizable VC markets due to the stark structural differences (e.g., Chen, 2023). The classification of *Seed* financing is similar to those used for the U.S. market, but we adjust the thresholds referring to the two million USD using the purchasing power adjustments to each country. Figure IA8 (Appendix) shows that the comparison countries did not experience a *Seed Boom* during the early 2010s.

[13] We add purchasing-power-adjusted measures of startup performance whenever the outcome variable refers to value-relevant performance targets. Unfortunately, we cannot study IP-related outcomes since IP data for non-U.S. startups is not fully available to us.

test the applicability of this argument, this section examines whether the *Seed Boom* indeed is associated with changes in the founding strategies of startups and investment patterns of VC investors.

***Seed*-backed startups:** We start by investigating the adaptive capacity of *Seed*-backed startups throughout the sample period. To do so, we measure general adjustments in organizational strategy by considering how startups' levels of differentiation upon incorporation have changed over time. The degree of differentiation refers to the extent startups offer value to (potential) customers in more distinct ways than their competitors. It can constitute a value-relevant and difficult-to-imitate resource for startups, given that more differentiated startups are usually better equipped to capture rents and grow (Koning *et al.*, 2022). Importantly, the actual positioning of startups is the outcome of repeated experimentation and learning efforts (e.g., Baker and Nelson, 2005; Kerr *et al.*, 2014b). Thus, structural changes towards more differentiated business strategies over time reflect that respective startups exercise operational flexibility enabling them to systematically come up with more distinct value propositions.

In particular, we utilize a novel startup-level measure of strategic differentiation introduced by Guzman and Li (2023) (henceforth GL-score). The score captures the distinctiveness of new firms' founding strategies by quantifying the text similarity in the value propositions stated on their websites at the time of startup creation relative to those of their closest competitors. The GL-scores are openly available and can be linked to Crunchbase data using the homepage URL information. Table IA11 (Appendix) contains descriptive statistics on the score for our sample startups.[14] We can retrieve the differentiation scores for 1,928 (692) of the *Seed*-backed startups in our (matched) sample. The relatively low matching rate can be explained by the incomplete overlap of our data with the original source and several missing URL entries of sample startups.

We conduct two important validation tests. First, we demonstrate that the patterns from our main analyses also apply to the subsample of startups for which we have retrieved the GL-scores. Consistent with the previous findings, we do not observe a differential changes in terms of performance outcomes, investment sizes, and age at initial investment throughout the *Seed Boom* for startups with a GL-score (Table IA12, Appendix).[15] Second, according to Guzman and Li (2023), startup differentiation at incor-

[14] Guzman and Li (2023) provide raw data on similarity scores that range from 0 to 1 for the five most similar webpages for both public and private firms. Following the authors' descriptions, we take these values, compute the average distance, and invert it by taking 1 minus the average similarity score. Higher GL-scores indicate a greater distance between the value propositions of a focal startup and its closest competitors, and vice versa. The statistics in Panel A of Table IA11 (Appendix) confirm that the GL-score distributions in our data closely resemble those in Guzman and Li (2023).

[15] These observations are important as they address potential concerns about the matching rate and apparent performance differences between startups with and without GL-scores. At the same time, we acknowledge that the null results may

poration is positively correlated with subsequent performance outcomes. This relationship is important for drawing inferences about the implications of changes in startup differentiation over time. Therefore, we validate this positive association in our data by replicating statistics from the original paper. Figure IA10 (Appendix) confirms the patterns displayed in Guzman and Li (2023): More differentiated startups are associated with more frequent and higher funding rates, whereas this relationship is weaker in terms of successful exits. Additionally, we show that more differentiated startups are more likely to obtain IP rights, potentially reflecting that having more distinct value propositions increases the possibility to introduce new technologies or brands.

Next, we turn to the question of whether startups' level of differentiation changed throughout the *Seed Boom* using the matched sample. We start by displaying the relationship between the *Seed*-intensity in the U.S. and the GL-scores in Figure 4 (Panel A). For both *Seed*-backed startups and the comparison group firms in the matched sample, the scatter plots suggest a positive association. However, the gradient of the linearly fitted values is much steeper for *Seed*-backed startups relative to the comparison group. These patterns are not sensitive to changing the GL-score definition, i.e., using the closest competitor instead of the average distance to the five closest competitors. Further, they mirror descriptive statistics on the changes in the distribution of the GL-score over time as in Panel B of Table IA11 (Appendix).

- Insert Figure 4 here -

To test this relationship more formally, we re-estimate regressions similar to Equation (1) and use the GL-score as the dependent variable. Panel B presents the corresponding results and confirms the positive and significant relationship between the stage of the *Seed Boom* and *Seed*-backed startups' level of differentiation at incorporation. This pattern remains qualitatively unchanged when deploying alternative model specifications and GL-score definitions (see Table IA13, Appendix). Overall, these results are consistent with the idea that *Seed*-backed startups pursued increasingly differentiated business strategies at incorporation throughout the *Seed Boom*. According to our interpretation, changes in differentiation reflects higher adaptive capacity, which appears to rise in a dynamic financing landscape.

VC investors: For a complementary perspective, we examine changes in investors' business strategies throughout the observation period. More specifically, we re-estimate Equation (1) using the investor-year panel introduced in Section 3.2. We follow our reasoning from Section 2 and consider investment

reflect reduced statistical power due to the smaller sample size.

characteristics that are related to risk-mitigating and risk-taking strategies as dependent variables. Considering risk-related measures is consistent with the observation that adjustments in risk behavior present a common strategy pursued by investors during times of changing market conditions. We measure risk-mitigation using the average deal size per investment (in logs), the total number of investment deals per year, the standard deviation in deal sizes, and the average number of co-investors per deal as a measure of investment syndication (see Gompers, 1995; Tian, 2011; Colombo *et al.*, 2019). Further, we quantify risk-taking by the average distance of investors to their targets (i.e., investors' monitoring ability) and the riskiness of the investment target, measured by startups' experience, age, and availability of IP rights (see Haeussler *et al.*, 2014; Ewens *et al.*, 2018; Azoulay *et al.*, 2020). Accordingly, the regressions include investor-level controls, state-year fixed effects, and investor fixed effects instead of firm-level controls, founding year fixed effects, and industry fixed effects.

The corresponding estimates in Table 5 support the notion that VCs increasingly apply diversification strategies to de-risk their investments throughout the *Seed Boom*. Panel A shows that for VC investors with *Seed* targets a higher *Seed*-intensity in the U.S. correlates with smaller deal sizes per investment (Column I) but more overall deals (Column II), higher standard deviations in deal sizes (Column III), and these deals are syndicated with more co-investors (Column IV). The results provide a consistent picture of VCs investors increasingly staging their investments in syndicated deals. In contrast, Panel B of Table 5 demonstrates that the *Seed Boom* cannot be associated with increased risk-taking. These findings remain qualitatively unchanged if we use alternative measures to quantify the phase of the *Seed Boom* (see Panel A of Table IA14, Appendix). Further, when repeating the analysis for the subsample of VCs that invested in *Seed* targets, we find that *Seed* investors not only increased diversification but they also de-risked their investments by selecting more experienced founding teams (Panel B of Table IA14).

- Insert Table 5 here -

Taken together, the observed patterns support the idea that investors indeed adjusted their business strategies throughout the *Seed Boom*, by increasingly pursuing de-risking strategies. Moreover, just like the findings on the founding strategies of *Seed*-backed startups, these insights are consistent with our theoretical considerations, suggesting that market dynamics, such as the *Seed Boom*, reveal the adaptive capacities of early-stage startups and their investors.

5 Conclusion

5.1 Discussion: Theoretical and practical considerations

How do VC-backed startups and their investors respond to rapidly changing market conditions? Our study sheds light on this question by examining startup performance, the founding strategies of new ventures, and the investment patterns of VCs. To do so, we utilize the context of the *Seed Boom* as a natural experiment in how entrepreneurial ecosystems respond to structural change. Through a theoretical lens, the implications of this development, which implied a shift in early-stage VC deals toward substantially younger and, hence, riskier startups are a priori unclear. On the one hand, a focus on risky investment targets increases the threat of investment misallocation. On the other hand, startups and investors should possess high adaptive capacities to navigate change in dynamic environments. Indeed, our analysis provides robust evidence that the *Seed Boom* did not significantly lower startup performance. Instead, we find that both startups and their corresponding investors substantially altered their business strategies, as measured by their founding and investment patterns.

This central finding is consistent with theoretical considerations of the resource-based view. Entrepreneurial firms are typically constrained in the resources needed to develop their business, while VCs are specialized intermediaries that can help startups mitigate these constraints. Conceptually, this implies that startups require the complementary resources of VCs to create value-relevant and inimitable resources that enable them to realize their potential: The equity investment of VCs softens organizational boundaries between startups and investors and enables the bundling of unique resources across the individual organizations. Dynamic environments call for adaptive capacities to adjust to changing market conditions. From the perspective of the resource-based view, such flexibility represents value-relevant resources that can eventually help market participants to maintain competitiveness even in dynamic markets. Our empirical analysis shows that startups and investors indeed exert a high degree of operational flexibility throughout the *Seed Boom*.

These findings contribute to the theoretical debate about the potential and limitations of entrepreneurial startups in generating new business ideas and shaping economic growth. As such, they seemingly contradict the theoretical perception of startups' liabilities of newness and smallness, which suggest a high degree of vulnerability among nascent firms, especially under rapidly evolving markets. Our interpretation is that newness and smallness also come along with benefits that allow young firms to navigate change in a dynamic entrepreneurial finance landscape. With this, our contribution to the theoretical literature lies in carving out and testing the opposing predictions regarding the potential performance implications of changes in the financing environment of startups.

Our analysis therefore not only speaks to academic discourses but also entails important managerial implications by shedding light on a structural shift in the U.S. venture capital market, the *Seed Boom*. From a business perspective, the results demonstrate the need for and the capability of major actors in the entrepreneurial ecosystem to adjust to fundamentally changing market conditions. With this, our analysis is also relevant as it moderates concerns raised by practitioners at the time about deteriorating startup performance once investments into specific market segments surge. The flexibility of startups and investors highlights the potential of market- and policy-based changes to foster startup growth by shaping entrepreneurial financing activities. Still, the results also call for caution, given that applying risk-mitigating strategies appears crucial to account for the inherent risks in these startups.

5.2 Generalizability and limitations

Our study leverages one specific empirical setting to study how startups and investors adapt to changing conditions in the entrepreneurial finance environment. As we show, the *Seed Boom* marks an extraordinary period during which startup activities substantially changed. Still, despite these natural limits, the implications of our findings are likely generalizable to other contexts.

As such, most of the observed patterns should generally apply in dynamic markets, irrespective of the specific case. For instance, the ability of investors to adapt to new circumstances is essential whenever market conditions change. Similarly, the ability of startups to pursue new business opportunities represents a critical resource for entrepreneurial success and, thus, will generally be vital in a dynamic environment. Examples of such dynamics may be shifts in funding of younger targets, as in our study, or trends toward older targets at comparable funding stages, as recent anecdotal evidence suggests.[16] Relatedly, our findings can also be indicative of activities at later stages of the VC cycle, given that the ability to adjust to changes in the market environment is not limited to a specific age or investment stage. For instance, the joint importance of critical resources possessed by startups and investors likely holds throughout the startup lifecycle, although the effects are particularly strong at early stages when the liabilities of newness and smallness are most binding.

[16] Illustrating the ongoing development of seed financing, the VC investor Jackie DiMonte described on LinkedIn that seed stage startups in the U.S. have the same average age in 2024 as Series A startups in 2014 (DiMonte, 2024).

Despite all efforts, our analysis has limitations. Startups in our sample endogenously select into *Seed* funding, which may partially explain performance and founding patterns throughout the *Seed Boom*. We acknowledge that choosing different comparison groups, as in Section 4.1 does not resolve this issue. However, it is beyond the scope of this study to examine the factors that explain such endogenous sorting. Relatedly, the evolving financial ecosystem has introduced a range of other options besides VCs, such as incubators, accelerators, angel investors, and various forms of crowdfunding (see Block *et al.*, 2018). Each option presents unique attributes and operational models, such that our findings may differ when analyzing the performance of startups that rely on these alternative sources. Finally, quantifying the relative importance of the specific factors that contributed to the *Seed Boom*, as introduced in Section 3.3, remains an important open facet. We leave these questions for future research.

5.3 Summary and conclusion

Access to funding is a key determinant for startup success. Consequently, structural changes in the financing environment of startups may have important implications for shaping the trajectories of nascent firms. Against this background, we investigate substantial transformations in the entrepreneurial finance landscape affect startup performance and adaptive capacity of market participants. To this end, we leverage data on a large set of U.S.-based startups and their corresponding investors to systematically document the changes in their business activities during the *Seed Boom*, a structural shift in the in the entrepreneurial finance environment that following the Great Financial Crisis in 2009. We embed this analysis in a series of theoretical considerations on the role of market dynamics in startup and investment activities. Over time, the way how entrepreneurial ventures and investors create and combine resources continuously changes as entrepreneurial ecosystem evolve. We argue that market dynamics may impair the identification and formation of complementary resource bundles, leading to deteriorating startup performance, but they may also induce adaptive investment practices that preserve such resource bundles. Our empirical analysis emphasizes that startup performance did not decline throughout the *Seed Boom* and that startups and investors pursued more differentiated value propositions and investment strategies, respectively. Rather than contradicting the liabilities of newness and smallness, our findings qualify concerns arising from these challenges by showing that young ventures can sustain performance in dynamic markets. Through this, our analysis enhances the understanding of how market participants respond to changing business environments.

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Tables from the main part

Table 1: Descriptive statistics on the sample of initially *Seed*-backed startups: Main variables and startup performance indicators

	Obs.	Mean	Std. dev.	p10	Median	p90
Age at initial round (in years)	4,894	0.790	0.606	0.038	0.712	1.638
Deal size of initial round (million USD)	4,894	0.950	2.061	0.070	0.775	1.825
Total number of investments	4,894	2.979	2.269	1	2	6
Total funds raised (million USD)	4,094	29.607	134.888	0.200	3.250	58.720
IPO	4,894	0.007	0.085	0	0	0
Acquisition (any)	4,894	0.225	0.418	0	0	1
Acquisition (high stakes)	4,894	0.014	0.118	0	0	0
Follow-on funding	4,894	0.661	0.473	0	1	1
10 mio. collected	4,894	0.265	0.441	0	0	1
50 mio. collected	4,894	0.087	0.281	0	0	0
Any IP right	4,894	0.283	0.450	0	0	1
Any patent filed	4,894	0.229	0.421	0	0	1

Notes: This table displays statistics on startup characteristics related to their investment activity and the main dependent variables, i.e., successful firm exits and funding rates. To avoid right censoring issues, we measure all variables within the first eight years after incorporation and include startups founded until 2015. The outcome variables are coded as indicator variables equal to one if any of the respective outcomes is achieved within the first eight years of startup life. The table reports respective numbers for the sample of all *Seed*-backed startups.

Table 2: Statistics on the prevalence of initially *Seed*-backed startups over time

	First-round deal type					
	Seed	Other VC	Total	*Seed*-ratio	Startup creation	*Seed*/creation ratio
2005	96	105	201	0.914	7,550	0.013
2006	123	160	283	0.769	8,118	0.015
2007	190	211	401	0.900	9,201	0.021
2008	195	231	426	0.844	9,980	0.020
2009	194	165	359	1.176	11,754	0.017
2010	329	222	551	1.482	13,091	0.025
2011	562	252	814	2.230	14,046	0.040
2012	769	274	1,043	2.807	15,770	0.049
2013	841	356	1,197	2.362	16,106	0.052
2014	884	473	1,357	1.869	16,425	0.054
2015	879	453	1,332	1.940	15,025	0.059

Notes: This table displays the absolute numbers of first-round equity investments targets in the U.S. from private investment funds. It distinguishes *Seed* from "Other" first-round equity investments targets and displays their relative occurrence in respective years. The fourth column (*Seed*-ratio) displays the ratio of initially *Seed*-backed startups divided by the number of other VC-backed sample startups. This variable measures the *Seed*-intensity over time and is used as main regressor in the estimations that test the performance implications of the *Seed Boom*; see also Equation (1). The last two columns display the number of newly created startups in the U.S. in the Crunchbase data and the share of initially *Seed*-backed startups as a fraction of these startup incorporation counts, respectively.

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Table 3: Regression estimations explaining *Seed* investments over time

Dependent variable:	*SeedRatio*				
	(I)	(II)	(III)	(IV)	(V)
Post^{Υ}	0.027	0.082***	0.158***	0.122***	0.018
	(0.025)	(0.026)	(0.025)	(0.022)	(0.020)
Definition of Υ	2008	2009	2010	2011	2012
Investor FE	Yes	Yes	Yes	Yes	Yes
Investor controls	Yes	Yes	Yes	Yes	Yes
R^2	0.555	0.557	0.560	0.558	0.555
N	5,292	5,292	5,292	5,292	5,292

Notes: The table displays regressions explaining the differential change in *Seed* investments, as defined in Section 3.1, over time. The data is an investor-year panel for the years 2005 until 2015, covering all investors in Crunchbase that invested in any of the sample firms during this observation period. The underlying OLS regression is: $SeedRatio_{it} = \gamma_i + \beta \text{Post}_t^{\Upsilon} + \gamma X_i + \varepsilon_{it}$, with the dummy Post^{Υ} being equal to one for any observations after 2008 (Column I), 2009 (Column II), 2010 (Column III), 2011 (Column IV), 2012 (Column V), respectively, and zero otherwise. The table displays the coefficients for β, capturing the change in *Seed* investments as of the respective year. The dependent variable is the share of *Seed* investments among all investments per year. The regressions control for investor fixed effects and X is a vector of investor-related controls. Standard errors are clustered on the investor level. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table 4: Matched sample probit regressions explaining startup performance throughout the *Seed Boom*

Panel A: Startup performance and *Seed* intensity

Dependent variable:	I(Performance indicators)								
	IPO	Acquisitions		Funds collected			IP generation		
		All	High stakes	Follow-on	10 million	50 million	Any IP	Patents	Trademarks
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)
SeedRatio × Seed	-0.121	0.139	-0.190	-0.194*	-0.085	-0.148	-0.031	-0.081	0.108
	(0.351)	(0.121)	(0.209)	(0.109)	(0.109)	(0.140)	(0.108)	(0.111)	(0.147)
Seed	-0.559	-0.334	0.134	0.360*	-0.488**	-0.149	-0.234	-0.166	-0.299
	(0.732)	(0.241)	(0.424)	(0.216)	(0.214)	(0.278)	(0.215)	(0.220)	(0.286)
SeedRatio	-0.121	-0.095	0.079	-0.194	-0.085	-0.148	-0.031	-0.081	0.108
	(0.351)	(0.117)	(0.213)	(0.109)	(0.109)	(0.140)	(0.108)	(0.111)	(0.147)
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Founding-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Chi^2	811.5	174.5	37.2	132.0	208.2	92.8	189.1	236.4	35.4
N	1,891	2,041	1,678	2,041	2,041	2,021	2,041	2,041	2,028

Panel B: Startup performance pre- and post-2010

Dependent variable:	I(Performance indicators)								
	IPO	Acquisitions		Funds collected			IP generation		
		All	High stakes	Follow-on	10 million	50 million	Any IP	Patents	Trademarks
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)
$Post^{2010}$ × Seed	-0.422	0.141	-0.681	-0.236	-0.094	-0.335	0.011	-0.058	0.083
	(0.480)	(0.180)	(0.473)	(0.157)	(0.158)	(0.206)	(0.156)	(0.160)	(0.216)
Seed	-0.579	-0.206	0.188	0.158	-0.575***	-0.186	-0.274*	-0.244*	-0.166
	(0.460)	(0.161)	(0.402)	(0.142)	(0.140)	(0.187)	(0.141)	(0.144)	(0.187)
$Post^{2010}$	-0.634	0.238	1.291**	0.347*	-0.020	0.296	-0.132	-0.228	0.273
	(0.617)	(0.212)	(0.557)	(0.180)	(0.181)	(0.245)	(0.178)	(0.182)	(0.239)
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Founding-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Chi^2	811.5	175.1	37.7	132.0	208.2	92.8	189.1	236.4	35.4
N	1,891	2,041	1,678	2,041	2,041	2,021	2,041	2,041	2,028

Notes: This table shows results from probit regressions that use a set of performance indicators as dependent variables. The sample is a matched sample of initially *Seed*-backed startups and other VC-backed startups. The regressions estimate Equation (1), using different performance indicators as dependent variable: the probability of a firm going public via an IPO (Column I), an acquisition (Column I), an acquisition with a reported purchasing price of at least 100 million USD (Column III), receiving any subsequent funding (Column IV), collecting at least 10 (Column V), or 50 million USD in funding (Column VI), generating any IP right (Column VII), filing a patent (Column VIII), or registering a trademark (Column IX), respectively. All outcome variables are measured eight years after incorporation and they are coded as binary indicators, which equal one if any of the performance outcomes is reached, and zero otherwise. In Panel A, the main regressor quantifying the *Seed Boom* is a continuous measure of the ratio of *Seed*-backed startups as a share of all startups in the sample (as displayed in Table 2). In Panel B, it is a dummy variable $Post^{2010}$, which is equal to one for all funding years as of 2010, and zero before. Standard errors are clustered at the firm level. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table 5: Changes of investment patterns of U.S. investors throughout the *Seed Boom*

Panel A: Regression estimates explaining changes in terms of diversification

Dep. variables:	log(avg. deal size)	log(nbr. deals)	SD deal size	Nbr. co-investors
	(I)	(II)	(III)	(IV)
$SeedRatio \times \text{Seed}^{\text{inv.}}$	-0.095***	0.187***	0.031**	0.239***
	(0.030)	(0.026)	(0.015)	(0.060)
Additional controls:				
Investor-level controls	Yes	Yes	Yes	Yes
Investor FE	Yes	Yes	Yes	Yes
State-year FE	Yes	Yes	Yes	Yes
N	16,776	16,776	16,776	16,776
R^2	0.77	0.77	0.59	0.56

Panel B: Regression estimates explaining changes in terms of risk-taking

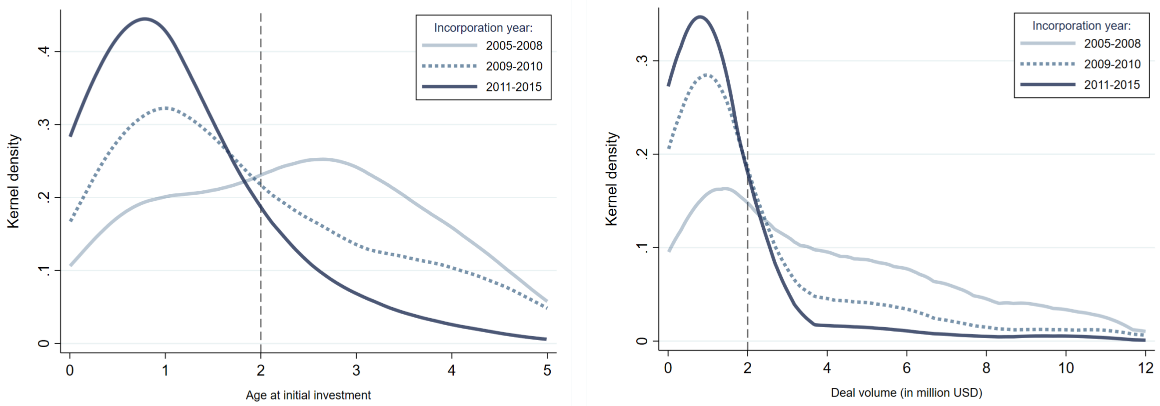
Dep. variables:	Local targets	Targets with IP	Experience (startups)	Experience (exits)
	(I)	(II)	(III)	(IV)
$SeedRatio \times \text{Seed}^{\text{inv.}}$	0.008	-0.014	-0.007	0.010
	(0.010)	(0.011)	(0.014)	(0.008)
Additional controls:				
Investor-level controls	Yes	Yes	Yes	Yes
Investor FE	Yes	Yes	Yes	Yes
State-year FE	Yes	Yes	Yes	Yes
N	16,776	16,776	12,424	12,424
R^2	0.70	0.53	0.47	0.44

Notes: The table displays regression estimates on the relationship between the *Seed Boom* and investment characteristics, comparing VC investors with and without *Seed* investments. The sample is an investor-year panel, comprising any VC that invested in any of the U.S.-based startups with an early-stage equity investment between 2005 and 2015. The regression specification is similar to those in Equation (1), but include investor-level controls, investor fixed effects and state-year fixed effects. The coefficient of interest on the interaction term captures the differential change in investment patterns of investors with *Seed* targets compared to those without *Seed* targets. As introduced in Section 4.2, the dependent variables in Panel A and B are measures of diversification and risk-taking, respectively. Standard errors (in parentheses below coefficients) are clustered on the investor-level. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Figures from the main part

Figure 1: Age and investment size distributions, first-stage investments in the U.S. (2005-2015)

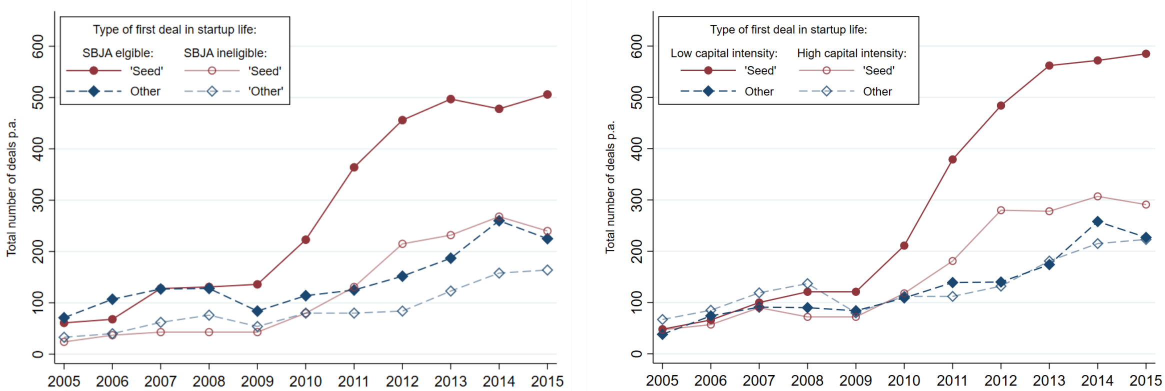
Panel A: Target age **Panel B:** Investment volumes



Notes: The figure displays the kernel density distributions of target age and investment size on first-round early-stage VC investments. Target age is calculated as the number of days differences between the official incorporation of a startup and the initial funding date divided by 365. Investment size is measured in million USD. The bandwidth in Panel A is 0.5 and 0.75 in Panel B. The dashed vertical line resembles the classification thresholds as defined in Section 3.1.

Figure 2: *Seed* funding intensity depending on startups exposure to policy- and market-based factors

Panel A: Startups subject to the 2010 SBJA **Panel B:** Startups with different capital-intensities

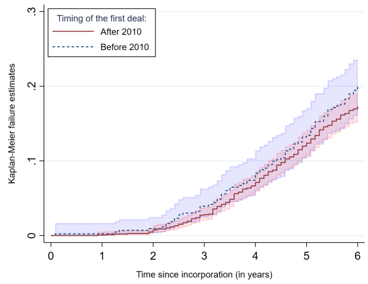


Notes: Panel A displays the development of first-round investments distinguishing U.S. firms that are active in sectors eligible to capital gains tax exemptions as stipulated in the SBJA as of September 2010 (as listed in Edwards and Todtenhaupt 2020). Investments further consider both *Seed* investments and all other first-round equity-backed startups ("Other"). The graph plots the annual number of deals by the respective four cohorts. All numbers are end-of-year total investment counts. Panel B is similar to before but distinguishes sectors with relatively low or high capital intensity, as defined in Section 3.3.

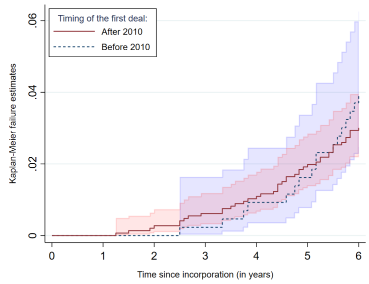
Figure 3: Exit and funding rates of *Seed*-backed targets before and after 2010s

Panel A: Exit rates

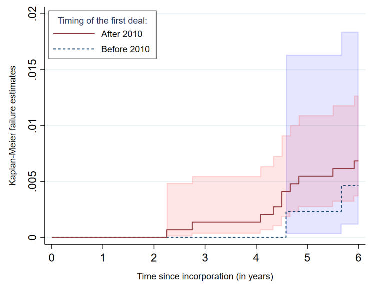
Acquisitions (all)



Acq. (high stakes)

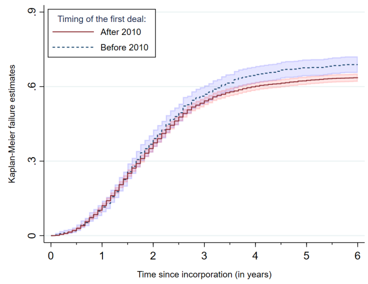


IPOs

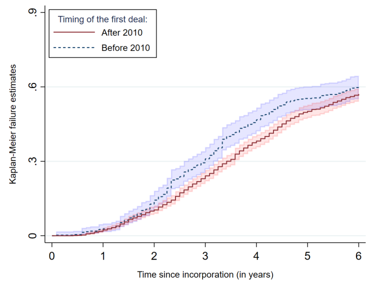


Panel B: Follow-on funding

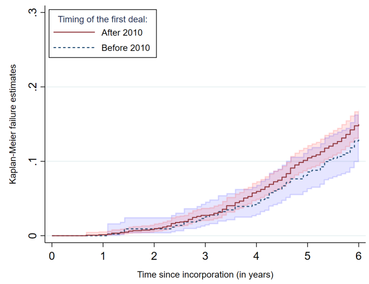
First follow-on deal



First 10 million USD



First 50 million USD

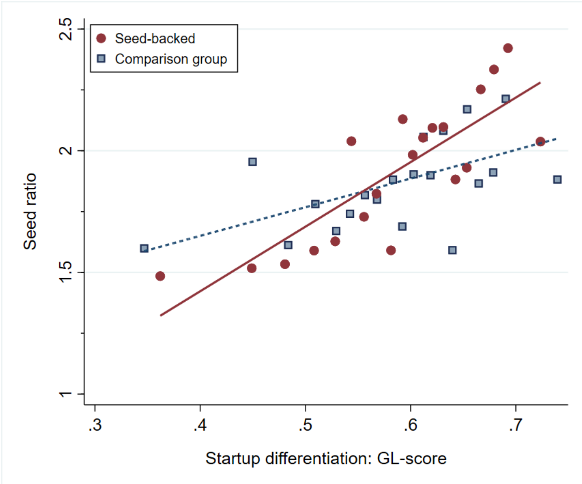


Notes: This figure displays the probability of a successful performance event to occur over time, comparing *Seed*-backed startups that received their initial funding before and after 2010, respectively. Performance refers to the probability of an acquisition, acquisitions with a reported purchasing price of at least 100 million USD, or a firm going public via an IPO (first row), and the probability of receiving follow-on investment, or a cumulative total amount of 10 or 50 million USD in external equity funding (second row). To avoid right censoring issues, we measure all variables within the six years after incorporation. The shaded areas around the hazard rates mark the 95% confidence intervals.

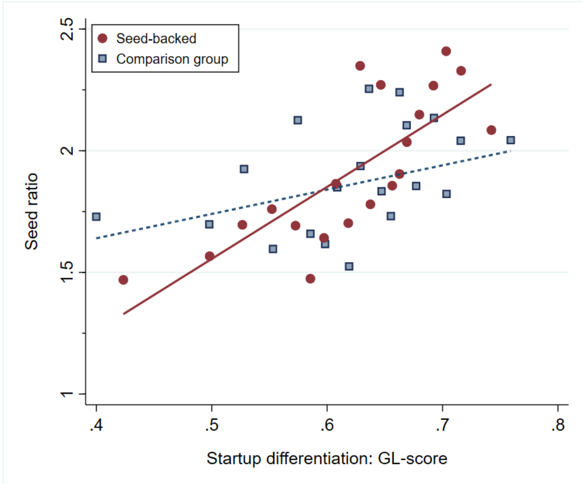
Figure 4: Startup founding strategies and the *Seed Boom*

Panel A: Binned scatterplots

Average distance to top-5 competitors



Distance to closest neighbor



Panel B: Regression analysis

Dependent variable:	*Startup Differentiation*			
	(I)	(II)	(III)	(IV)
$SeedRatio_{\tau}$ × Seed	0.022**	0.022*		
	(0.010)	(0.012)		
$Post_{\tau}^{2010}$ × Seed			0.031**	0.035**
			(0.015)	(0.018)
Seed	-0.029	-0.022	-0.006	-0.013
	(0.018)	(0.019)	(0.011)	(0.013)
Differentiation type:	Avg. distance	Cl. neighbor	Avg. distance	Cl. neighbor
Firm-level controls	Yes	Yes	Yes	Yes
Founding-year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
R^2	0.26	0.24	0.25	0.24
N	664	664	664	664

Notes: This figure presents evidence on the relationship between startups' founding strategies and the *Seed Boom*. To measure these strategies, we adopt the differentiation scores at incorporation from Guzman and Li (2023). We use the average distance in the value propositions as stated on the webpages of focal startups relative to their top-5 competitors and closest neighbor, respectively. Competitors can be any private firm and we use the matched sample introduced in Section 4.1. Panel A displays binned scatterplots on the *Seed* ratio, as used before, and startups GL-scores for initially *Seed*-backed startups and comparison group firms. Panel B displays estimates on regressions that explain this association in a multivariate setting, following the specification as defined in Equation (1), using the GL-scores as the dependent variables. Only here, we define the *Seed* ratio based on the founding year (i.e., and not calendar year). Standard errors (in parentheses below coefficients) are clustered on the investor-level. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

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Table IA1: Overview on Crunchbase labels of sample data

Panel A: Crunchbase investment type categories of sample startups by type

	Seed (first-round)		Other (first-round)	
Crunchbase label	Obs.	in %	Obs.	in %
Pre-seed	196	4.00	19	0.71
Angel	269	5.50	23	0.86
Seed	3,821	78.08	511	19.17
Venture capital	444	9.07	1,271	47.67
Series unkown	164	3.35	842	31.58
Total	4,894	100.00	2,666	100.00

Panel B: Crunchbase investor type categories of sample startups (in %)

	Target type (first-round)		
Crunchbase label	All	*Seed*	Other VC
Venture Capitalist	77.13	75.78	80.51
Accelerator	7.77	9.87	2.52
CVC	4.30	3.78	5.58
Angel	3.29	3.53	2.70
Incubator	0.60	0.58	0.65
Other	2.65	2.37	3.37
Unkown	4.25	4.08	4.68

Notes: Panel A displays the Crunchbase investment type categories (mnemonic `investment_type`) assigned to first-round deals obtained from startups in our sample. Columns I and II distinguish startups that receive first-round investments at very early stages (*Seed*) and at relatively later points in time (Other VC). Panel B displays the Crunchbase investor type categories (mnemonic `investor_type`) assigned to each investor of all deals listed in Panel A.

Table IA2: List of variables

Variables	Definitions
Main regressors	
Seed	Dummy variable taking a value of 1 for *Seed*-backed startups, i.e., startups that received a first round of equity investments from a VC fund with a maximum deal size of two million USD within the first two years after their incorporation; value 0 is assigned to startups that receive first round equity investments from VC with a volume of more than two million USD and at a later age than two years.
SeedRatio	Continuous variable measuring the *Seed*-intensity in the US per year. *Seed*-intensity refers to the fraction of *Seed* deals among total early-stage investments, as displayed in Table 2. Without subscript, the reference year is the startups' funding year. With the subscript τ, the reference year is the year of incorporation. For analyses that use the investor-level data, the *Seed* ratio refers to the share of *Seed* investments among total investments by respective investors in a given.
Post$^{\Upsilon}$	Dummy variable equal to 1 for all years after Υ, $\forall \in$ [2008, 2012], and 0 for the years up until Υ. Without subscript, the reference year is the startups' funding year. With the subscript τ, the reference year is the year of incorporation.
$Seed^{inv.}$	Dummy variable taking a value of 1 for VC funds that invested in *Seed* funding (as defined before) and 0 otherwise.
Main dependent variables	
*Seed*deals ratio	Share of *Seed* investments as a fraction of total investments of a focal VC investor in a given year.
log(Seed-deals)	Continuous measure of the total number (+1) of *Seed* investments (in logs) of a focal VC investor in a given year.
IPO	Dummy variable taking a value of 1 if the startup exited via initial public offering within in the first eight years after incorporation.
Acquisitions	Dummy variable taking a value of 1 if the startup exited via an acquisition within in the first eight years after incorporation. We use two variants of this variable: *All*, referring to acquisitions of any deal volume (including unknown volumes), and *High stakes* referring to acquisitions with a minimum valuation of 100 million USD.
Funds collected	Dummy variable taking a value of 1 if the startup has raised a given amount of total funding within in the first eight years after incorporation. We use three variants of this variable: *Follow-on funding* being an indicator equal to 1 if the startup was able to raise any follow-on funding within the first eight years, and 10million or 50million indicating whether the focal startup has raised 10 or 50 million USD in total funding within the first eight years.
IP generation	Dummy variable taking a value of 1 if the startup filed for an intellectual property right within in the first eight years after incorporation. We use three variants of this variable, indicating whether the focal startup filed for a patent, registered a trademark, or filed for any IP right (patent or trademark).

(continued on next page)

Table IA2: List of variables (*continued*)

Variables	**Definitions**
Main dependent variables (*continued*)	
Startup Differentiation	Continuous variable measuring the level of startup differentiation at incorporation, adopted from Guzman & Li (2023). It captures the text similarity in the value propositions stated on startups websites at startup incorporation relative to the value propositions stated on the websites of their closest competitors. We take the original similarity scores that range from 0 to 1, compute the average distance of the five most similar webpages for both public and private firms, and invert it by taking 1 minus the average similarity score. Hence, higher differentiation indicate a greater distance between the value propositions of a startup and its closest competitors, and vice versa.
log(avg. deal size)	Continuous measure of the average investment size of all investment deals per year per investor (in logs).
log(nbr. deals)	Continous measure of the total number of investment deals per year per investor (in logs).
SD deal size	Continous measure of the standard deviation of the investment sizes of all investment deals per year per investor.
Nbr. co-investors	Continous measure of the average number of co-investors per deal in a given year, measure the syndication of deals.
Local targets	Dummy variable taking a value of 1 if investors and targets are headquartered in the same state, and 0 otherwise.
Targets with IP	Share of targets that hold IP rights (patents and trademarks) at the time of investment.
Experience (startups)	Number of startups created by the founding team prior to the incorporation of the focal startup.
Experience (exits)	Dummy variable taking a value of 1 if at least one founder created a startup prior to the incorporation of the focal startup with a successful exit (IPO or acquisition), and 0 otherwise.
Other regressors (in robustness tests displayed in the Appendix)	
$Seed^{CB}$	Dummy variable taking a value of 1 for startups with a first-round equity investment labelled as "Seed" investment in the Crunchbase data (mnemonic: investment_type), and 0 otherwise.
Exposed	Dummy variable taking a value of 1 for initially *Seed*-backed startups (as defined before) that are active in a sector that is both eligible for tax exemption under the SBJA and classifies as low capital-intensive, and 0 otherwise.
$Seed^{US}$	Dummy variable taking a value of 1 for initially *Seed*-backed startups (as defined before) that are headquartered in the US, and 0 otherwise.
I(GL-score)	Dummy variable taking a value of 1 for all initially *Seed*-backed startups (as defined before) for which a Guzman-Li differentiation score is available, and 0 otherwise.
Other variables used in the analysis	
Target age	Age at initial round (in years): Differences in days (divided by 365) between the official incorporation of a startup and the date of the first equity investment deal that the focal startup received from a VC.
Founder age	Difference in days between their first university degree and the date of incorporation of the respective startup (divided by 365).

Table IA3: Business activities of sample startups, as share of total (in %)

	First-round equity investment type		
	All startups	**Other**	**'Seed'-backed**
Software	36.44	28.99	40.70
Internet Services	28.15	20.82	32.35
Media & entertainment	25.02	18.05	29.02
Information technology	19.94	20.61	19.56
Mobile	17.62	12.54	20.53
Healthcare	17.30	22.90	14.10
Data analytics	16.02	12.16	18.23
Hardware	15.61	19.36	13.47
Commerce & shopping	14.11	9.45	16.78
Sales & marketing	13.95	11.64	15.27
Science & engineering	13.57	18.60	10.69
Community & lifestyle	12.94	8.21	15.65
Financial services	9.65	8.59	10.25
Apps	8.95	5.61	10.87
Advertising	7.45	6.75	7.85
Content & publishing	7.37	5.58	8.39
Biotechnology	7.11	11.78	4.44
Professional services	6.58	6.96	6.37
Consumer electronics	6.37	7.38	5.79
Design	6.10	4.64	6.94
Video	5.75	4.57	6.42
Artificial intelligence	5.51	3.74	6.53
Payments	5.06	3.95	5.69
Manufacturing	4.94	8.52	2.90
Security	4.73	5.51	4.28
Education	4.68	3.95	5.10
Cloud	4.58	4.75	4.48
Administrative services	3.93	3.60	4.13
Messaging & telecommunication	3.76	2.46	4.50
Food & beverages	3.57	4.26	3.17
Sustainability	3.57	6.10	2.12
Transportation	3.54	3.57	3.53
Energy	3.51	6.27	1.92
Real estate	3.23	2.91	3.41
Sports	3.06	2.60	3.33
Platforms	3.01	1.70	3.77
Travel & tourism	2.89	2.60	3.05
Clothing & apparel	2.74	1.70	3.33
Gaming	2.57	2.25	2.76

Notes: This table displays all self-reported business fields in the sample for which the aggregate share ("*All startups*") is at least 2.5%. The table further distinguishes among startups that receive financing within the first two years of incorporation and afterwards. The main categories are not mutually exclusive. "Other" refers to startups with a first round equity investment of at least two million USD and a minimum age of two years. *Seed* refers to startups with first round equity investments of less than two million USD and that are younger than two years at the respective first round.

Table IA4: Investor and startup characteristics of first-round targets (*Seed* vs. "Other")

Mean values					
Investor characteristics:	**Seed**	**Other**	**Startup characteristics:**	**Seed**	**Other**
Sydicated investment	0.539	0.439	*Founder-specific characteristics:*		
Total number of investors	2.787	1.950	Serial entrepreneur	0.282	0.156
US-based investors	0.805	0.817	Prior exit	0.064	0.041
Same state investors	0.517	0.412	Average age (since first degree)	13.438	16.095
CVC participation	0.040	0.073	*Patent characteristics:*		
Investor Age (since incorporation)	7.873	13.142	Pre-investment filings (dummy)	0.091	0.331
Log(Rank)	12.145	12.165	Log(Patent filings pre-investment)	0.129	0.516

Notes: This table displays statistics on investor- and startup-specific characteristics for both startups that receive first-time investments in form of *Seed* financing and those startups ("Other") that receive first-time investments of more than two million USD and at a minimum age of two years. The displayed figures refer to the mean value of respective startup categories at the first funding round for the following variables: the share of investments conducted by a syndicate of investors, the total number of initial investors at initial financing round, the share of investors with a registered address in the U.S., the share of investors with a registered address in the home state of the target, the share of CVC investors, investor's age calculated based on the year of incorporation, and logarithm of Crunchbase rank as a measure of investor's prominence. Startup characteristics include founder entrepreneurship experience (serial entrepreneur), the success of prior founder startups (prior exit), founders' average age since their first degree, and startups' pre-investment patenting activities. The patenting characteristics comprise the probability of filing a patent prior to first founding round and the logarithm of number of patents filed before the first investment.

Table IA5: Robustness tests for Table 3

Panel A: Using continuous measure of Seed-deals as dependent variable

Dependent variable:	log(*Seed*–deals)				
	(I)	(II)	(III)	(IV)	(V)
Post$^{\Upsilon}$	0.003	0.082***	0.234***	0.207***	0.049**
	(0.029)	(0.031)	(0.030)	(0.028)	(0.025)
Definition of Υ	2008	2009	2010	2011	2012
Investor FE	Yes	Yes	Yes	Yes	Yes
Investor controls	Yes	Yes	Yes	Yes	Yes
R^2	0.668	0.669	0.674	0.673	0.668
N	5,292	5,292	5,292	5,292	5,292

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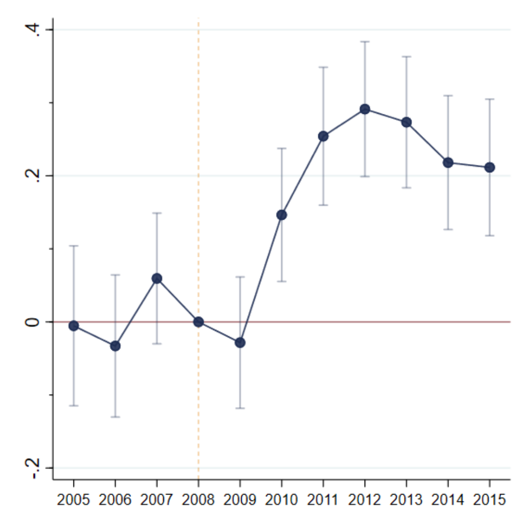
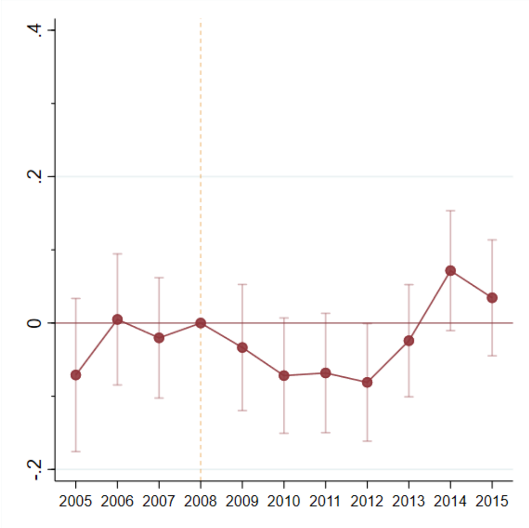
Table IA5: Robustness tests for Table 3 (*continued*)

Panel B: Event study-type coefficient plots

Seed investments:



Other early-stage deals:



Panel C: Using Crunchbase classifications for *Seed* investments

Dependent variable:	*Seed*–deal Share				
	(I)	(II)	(III)	(IV)	(V)
Post$^{\Upsilon}$	0.018	0.054**	0.109***	0.158***	0.043**
	(0.022)	(0.023)	(0.023)	(0.021)	(0.020)
Definition of Υ	2008	2009	2010	2011	2012
Investor FE	Yes	Yes	Yes	Yes	Yes
Investor controls	Yes	Yes	Yes	Yes	Yes
R^2	0.650	0.651	0.653	0.655	0.651
N	5,292	5,292	5,292	5,292	5,292

Notes: The tables display robustness tests on regression estimations explaining *Seed* investments over times, as displayed in Table 3. Panel A repeats the same analysis as before, but uses the total number of Seed investments by each investor (measured as rounds +1 in logs.). Panel B plots regression coefficients from event study-type regressions. The specification is similar to Panel A, only here the Post-dummy is exchanged with a set of dummies for each year. The year of the financial crisis, 2008, is the reference period. The left figure displays the coefficients using the number of *Seed* investments (+1 in logs) as dependent variable. The right figure uses the number of all other investments by respective VCs as dependent variable (+1 in logs). The whiskers span the 99 percent confidence intervals. Panel C is equivalent to Table 3, but uses the Crunchbase labels to classify *Seed* investments to mitigate concerns that our classification approach of investment types drives the observed patterns. Standard errors are clustered at the firm level. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table IA6: List of low-capital-intensive sectors with subcategories

Main activity	Subfields
Software	3d technology; application performance management; augmented reality; billing; bitcoin; browser extensions; cad; cms; computer vision; consumer software; contract management; crm; cryptocurrency; data center automation; data storage; developer apis; developer platforms; developer tools; document management; drone management; electronic design automation (eda); embedded software; embedded systems; enterprise resources planning (erp); enterprise software; ethereum; file sharing; iaas; image recognition; machine learning; marketing automation; meeting software; mooc; open source; paas; presentation software; presentations; productivity tools; qr codes; retail technology; robotics; saas; sales automation; scheduling; sex tech; simulation; sns; social crm; software engineering; task management; transaction processing; virtual assistant; virtual currency; virtual desktop; virtual goods; virtual reality; virtual world; virtualization
Data analytics	Artificial intelligence; big data; bioinformatics; biometrics; business intelligence; consumer research; data integration; data mining; data visualization; database; intelligent systems; location based services; machine learning; market research; natural language processing; predictive analytics; product research; quantified self; speech recognition; test and measurement; text analytics; usability testing
Internet	Darknet; domain registrar; e-commerce platforms; e-learning; ediscovery; edtech; email; internet of things; isp; location based services; music streaming; online forums; product search; online portals; social media; social media management; social network; web development
Cloud	Cloud computing; cloud data services; cloud infrastructure; cloud management; cloud storage; private cloud
Platforms	Android; Facebook; Google; Google glass; iOs; Linux; MacOs; Nintendo; operating systems; Playstation; Roku; Tizen; Twitter; webOs; Windows; Windows phone; xBox
Apps	App discovery; apps; consumer applications; enterprise applications; mobile apps; reading apps; web apps
Online security	Cloud security; cyber security; drm; e-signature; facial recognition; fraud detecion; identity management; intrusion detection; network security; penetration testing; privacy
Payments	Billing; mobile payments; payments; transaction processing; virtual currency; fintech

Notes: This table lists all main business fields and the corresponding subfields, which we consider as low-capital-intensive sectors. Specifically, we obtain the main fields from the industries listed for Facebook, Amazon, Apple, Netflix, and Google in Crunchbase. We then retrieve all corresponding subfields listed for these main fields in Crunchbase. We exclude fields that cannot be associated with high tech, digital sectors. The classification is based on Crunchbase's business fields as of November 2022. The main categories are not mutually exclusive, thus we omit multiple entries.

Table IA7: Descriptive statistics on successful startup exits via acquisitions and IPOs

	Total	**Acquisition**	**IPO**
Incidence	2,537	2,359	178
Incidence - *Seed* only (in %)	1,541 (60.7)	1,541 (65.3)	80 (44.9)
Timelag until exit (*Seed* only):			
- mean	7.21 (5.62)	7.03 (5.47)	9.59 (8.43)
- median	6.58 (5.05)	6.37 (4.93)	9.18 (8.49)

Notes: The table displays the incidences of successful firm exits via acquisitions and IPOs and their funding history for the full Crunchbase sample on U.S.-based startups that received first-round equity investments by equity funds between 2005 and 2015. Specifically, it shows the number of exits both for the full sample and for *Seed*-backed startups. The table also displays the average and median duration in years (i.e., days/365) between the incorporation date and the exits of respective startups.

Table IA8: Regression estimations on the performance patterns throughout the *Seed Boom*

Panel A: Startup performance and *Seed* intensity

Dependent variable:	I(Performance indicators)								
	IPO	Acquisitions		Funds collected			IP generation		
		All	High stakes	Follow-on	10 million	50 million	Any IP	Trademarks	Patents
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)
SeedRatio	-0.011	-0.057	-0.386*	-0.059	-0.131	-0.069	-0.137*	-0.108	-0.031
	(0.257)	(0.079)	(0.199)	(0.078)	(0.081)	(0.105)	(0.079)	(0.083)	(0.114)
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Founding-year FE	Yes	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Chi^2	188.2	245.2	66.5	325.7	451.7	247.7	308.0	390.8	49.5
N	4,856	4,891	4,891	4,894	4,894	4,891	4,894	4,856	4,894

Panel B: Startup performance pre- and post-2010

Dependent variable:	I(Performance indicators)								
	IPO	Acquisitions		Funds collected			IP generation		
		All	High stakes	Follow-on	10 million	50 million	Any IP	Trademarks	Patents
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)
Post^{2010}	-0.073	-0.137	-0.293	0.232	-0.087	-0.186	-0.038	0.037	-0.066
	(0.612)	(0.148)	(0.274)	(0.152)	(0.150)	(0.200)	(0.149)	(0.210)	(0.155)
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Founding-year FE	Yes	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Chi^2	178.0	245.5	65.8	325.1	450.3	247.8	304.1	388.6	49.5
N	4,856	4,891	4,891	4,894	4,894	4,891	4,894	4,856	4,894

Notes: This table presents conditional probit regressions explaining potential performance implications of the *Seed Boom*, estimating the following equation: $I(P_i) = \beta SeedBoom + \gamma X_{it} + \beta_t + \beta_j + u_{it}$. The sample is initially *Seed*-backed startups only. All performance indicators are coded as dummy variables equal to one for startups that successfully exit via IPO (Column I), exit via an acquisition (Column II), exit via an acquisition with minimum 100 million USD valuation (Column III), have obtained follow-on funding (Column IV), collected at least 10 or 50 million USD (Columns V and VI), or have filed at least one patent or trademark (Column VII), trademark (Column VII), or patent (Column VIII) within the first eight years after incorporation. Panel A shows results from probit regressions in which the main explanatory variable, *SeedBoom*, is a continuous variable measuring the stage of *SeedBoom*. Panel B is similar but uses a *Post*-dummy. All variables are defined in Table IA2 (Appendix). Standard errors are clustered at the firm level. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table IA9: Robustness tests on the baseline probit regressions in Table 4

Panel A: Startup performance pre- and post-2009

Dependent variable:	I(Performance indicators)								
	IPO	Acquisitions		Funds collected			IP generation		
		All	High stakes	Follow-on	10 million	50 million	Any IP	Patents	Trademarks
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)
$Post^{2009}$ × Seed	-0.132	-0.049	-0.654*	-0.372**	-0.250	-0.309	0.078	0.003	0.127
	(0.599)	(0.197)	(0.335)	(0.179)	(0.178)	(0.228)	(0.177)	(0.181)	(0.250)
Seed	-0.744	-0.059	0.583**	0.278*	-0.471***	-0.185	-0.343**	-0.309*	-0.197
	(0.557)	(0.180)	(0.250)	(0.164)	(0.161)	(0.209)	(0.163)	(0.166)	(0.218)
$Post^{2009}$	-0.349	0.369*	0.624*	0.527***	0.395**	0.320	0.026	-0.004	0.186
	(0.645)	(0.220)	(0.297)	(0.196)	(0.193)	(0.242)	(0.191)	(0.196)	(0.251)
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Founding-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Chi^2	964.2	173.2	53.0	134.3	210.4	95.3	189.9	236.4	34.5
N	1,891	2,041	1,678	2,041	2,041	2,021	2,041	2,041	2,028

Panel B: Startup performance pre- and post-2011

Dependent variable:	I(Performance indicators)								
	IPO	Acquisitions		Funds collected			IP generation		
		All	High stakes	Follow-on	10 million	50 million	Any IP	Patents	Trademarks
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)
$Post^{2011}$ × Seed	-0.501	0.185	-0.448	-0.214	-0.167	-0.235	0.074	-0.012	0.183
	(0.449)	(0.163)	(0.351)	(0.145)	(0.146)	(0.191)	(0.145)	(0.149)	(0.206)
Seed	-0.561	-0.202	0.030	0.151	-0.539***	-0.273	-0.330***	-0.298**	-0.215
	(0.422)	(0.146)	(0.296)	(0.128)	(0.125)	(0.167)	(0.126)	(0.129)	(0.173)
$Post^{2011}$	-1.071**	-0.109	0.360	0.055	0.028	0.235	0.047	-0.004	0.206
	(0.539)	(0.187)	(0.422)	(0.161)	(0.163)	(0.220)	(0.160)	(0.163)	(0.222)
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Founding-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Chi^2	635.2	171.9	36.9	131.9	208.8	94.1	189.8	236.5	36.4
N	1,891	2,041	1,678	2,041	2,041	2,021	2,041	2,041	2,028

Panel C: Using Crunchbase labels for investment classifications

Dependent variable:	I(Performance indicators)								
	IPO	Acquisitions		Funds collected			IP generation		
		All	High stakes	Follow-on	10 million	50 million	Any IP	Patents	Trademarks
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)
$SeedRatio$ × $Seed^{CB}$	-0.749**	-0.015	-0.530***	-0.137	-0.106	-0.189	-0.001	-0.003	0.127
	(0.350)	(0.110)	(0.197)	(0.101)	(0.104)	(0.135)	(0.102)	(0.105)	(0.143)
$Seed^{CB}$	0.987	-0.030	0.684*	0.231	-0.344*	0.087	-0.222	-0.248	-0.346
	(0.640)	(0.217)	(0.371)	(0.202)	(0.205)	(0.273)	(0.203)	(0.208)	(0.288)
$SeedRatio$	-0.282	0.007	0.207	0.091	0.005	0.077	0.042	0.010	0.062
	(0.272)	(0.105)	(0.198)	(0.092)	(0.092)	(0.123)	(0.092)	(0.095)	(0.122)
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Founding-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Chi^2	635.2	171.6	39.6	131.9	208.8	94.1	189.8	236.5	36.4
N	1,891	2,041	1,678	2,041	2,041	2,021	2,041	2,041	2,028

(continued on next page)

Table IA9: Robustness tests (*continued*)

Panel D: *Seed* intensity and startup performance in highly affected markets

Dependent variable:	I(Performance indicators)							
	Acquisitions		Funds collected			IP generation		
	All	High stakes	Follow-on	10 million	50 million	Any IP	Patents	Trademarks
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
SeedRatio × Seed	-0.082	-0.165	-0.259	-0.165	-0.340	-0.143	-0.154	-0.078
	(0.178)	(0.273)	(0.166)	(0.167)	(0.221)	(0.167)	(0.170)	(0.217)
Seed	-0.000	0.518	0.460	-0.449	0.459	0.128	0.198	-0.080
	(0.356)	(0.513)	(0.331)	(0.332)	(0.452)	(0.333)	(0.341)	(0.403)
SeedRatio	0.006	-0.278	0.194	0.146	0.328	0.228	0.238	0.132
	(0.165)	(0.268)	(0.149)	(0.154)	(0.207)	(0.150)	(0.153)	(0.207)
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Founding-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Chi^2	98.0	53.6	63.3	126.7	60.0	110.8	111.7	28.7
N	983	716	977	983	969	983	983	964

Panel E: Startup performance in highly affected markets before and after 2010

Dependent variable:	I(Performance indicators)							
	Acquisitions		Funds collected			IP generation		
	All	High stakes	Follow-on	10 million	50 million	Any IP	Patents	Trademarks
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
$Post^{2010}$ × Seed	-0.381	-0.685*	-0.244	-0.172	-0.574*	-0.077	-0.094	-0.153
	(0.277)	(0.414)	(0.243)	(0.246)	(0.343)	(0.243)	(0.247)	(0.299)
Seed	0.104	0.512	0.170	-0.612***	0.283	-0.034	0.024	-0.111
	(0.251)	(0.356)	(0.220)	(0.222)	(0.328)	(0.219)	(0.225)	(0.247)
$Post^{2010}$	0.707**	0.508	0.206	0.068	0.312	-0.092	-0.068	0.334
	(0.321)	(0.489)	(0.277)	(0.285)	(0.405)	(0.276)	(0.282)	(0.345)
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Founding-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Chi^2	100.6	54.0	62.2	125.9	62.5	109.2	109.9	28.1
N	983	716	977	983	969	983	983	964

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Table IA9: Robustness tests (*continued*)

Panel F: Triple-differences estimation on startup performance in highly affected markets

Dependent variable:	I(Performance indicators)								
	IPO	Acquisitions		Funds collected			IP generation		
		All	High stakes	Follow-on	10 million	50 million	Any IP	Patents	Trademarks
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)
SeedBoom × Seed × Exposed	-0.668	-0.210	0.204	-0.118	-0.048	-0.294	-0.172	-0.237	0.139
	(0.438)	(0.207)	(0.321)	(0.191)	(0.191)	(0.248)	(0.191)	(0.196)	(0.266)
Seed × Exposed	1.281	0.365	-0.618	0.181	0.122	0.829*	0.377	0.525	-0.164
	(1.006)	(0.409)	(0.654)	(0.383)	(0.381)	(0.498)	(0.381)	(0.390)	(0.533)
SeedBoom × Exposed	-0.093	0.109	-0.108	0.120	0.131	0.322*	0.157	0.246	-0.247
	(0.321)	(0.172)	(0.205)	(0.152)	(0.152)	(0.195)	(0.153)	(0.156)	(0.205)
SeedBoom × Seed	-0.013	0.238	-0.265	-0.156	-0.077	-0.071	0.037	0.012	0.054
	0.407)	(0.158)	(0.277)	(0.138)	(0.137)	(0.173)	(0.137)	(0.141)	(0.180)
Exposed	0.088	-0.188	0.460	-0.249	-0.380	-0.884**	-0.450	-0.578*	0.194
	(0.798)	(0.339)	(0.437)	(0.307)	(0.305)	(0.390)	(0.307)	(0.315)	(0.410)
Seed	-0.795	-0.503	0.382	0.310	-0.512*	-0.404	-0.376	-0.374	-0.221
	(0.853)	(0.309)	(0.564)	(0.273)	(0.268)	(0.339)	(0.270)	(0.276)	(0.360)
SeedBoom	-0.506	-0.141	0.128	0.083	-0.037	-0.013	0.007	-0.036	0.168
	(0.387)	(0.146)	(0.253)	(0.119)	(0.118)	(0.155)	(0.118)	(0.121)	(0.147)
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Founding-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Chi^2	964.2	175.6	85.2	134.3	210.4	95.3	189.9	236.4	34.5
N	1,891	2,039	1,676	2,039	2,039	2,019	2,039	2,039	2,026

Notes: This table shows results from robustness tests on the estimates displayed in Table 4. All specifications use the same model specifications and data. Panel A and B use an alternative measure to delineate the pre- and post-boom periods, namely, using 2009 and 2011 instead of 2010 (in Panel B of Table 4). Panel C uses the Crunchbase definition of investment types to classify *Seed*-backed startups. Panels D and E estimate the same specifications as in Panels A and B of Table 4, using a subsample of startups that operate in business fields that are subject to both SBJA and are low-capital-intensive. These sectors are particularly exposed to the changes in the environmental landscape. We cannot estimate regressions using IPOs as the dependent variable due to too few observations. Panel F is similar to the baseline estimation but introduces a triple interaction using the indicator *Exposed*, which is equal to one for all startups from SBJA-eligible and low-capital-intensive sectors, and zero otherwise. Standard errors are clustered at the firm level. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table IA10: The performance of U.S.- and non-U.S.-based startups throughout the U.S. *Seed Boom*

Panel A: Performance of U.S.- and non-U.S. startups and *Seed* intensity

Dependent variable:	I(Performance indicators)								
	IPO	Acquisitions			Funds collected				
		All	High stakes	High st.^{PPP}	Follow-on	10 mill.	10 mill.^{PPP}	50 mill.	50 mill.^{PPP}
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)
SeedRatio × $Seed^{US}$	0.038	-0.052	0.317	-0.027	-0.214***	-0.203**	-0.261***	-0.164	-0.127
	(0.241)	(0.085)	(0.274)	(0.265)	(0.077)	(0.086)	(0.088)	(0.119)	(0.126)
$Seed^{US}$	-0.155	0.392**	0.200	0.935	0.655***	0.925***	1.105***	0.694***	0.695***
	(0.452)	(0.174)	(0.428)	(0.518)	(0.166)	(0.181)	(0.186)	(0.246)	(0.261)
SeedRatio	-0.355	0.005	-0.195	0.210	0.166	0.069	0.083	0.132	0.137
	(0.378)	(0.120)	(0.487)	(0.455)	(0.102)	(0.125)	(0.130)	(0.177)	(0.195)
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Founding-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Chi^2	12.9	148.1	113.1	123.5	253.1	147.1	181.0	72.9	88.0
N	2,224	3,266	1,927	1,827	3,266	3,266	3,266	3,266	3,266

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Table IA10: Performance of U.S.- and non-U.S.-based startups (*continued*)

Panel B: Performance of U.S.- and non-U.S. startups pre- and post-2010

Dependent variable:	I(Performance indicators)								
	IPO	Acquisitions			Funds collected				
		All	High stakes	High st.^{ppp}	Follow-on	10 mill.	10 mill.^{ppp}	50 mill.	50 mill.^{ppp}
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)
$Post^{2010}$ × Seed^{US}	0.052	-0.030	0.486	0.027	-0.351***	-0.373***	-0.441***	-0.388*	-0.359*
	(0.349)	(0.134)	(0.364)	(0.438)	(0.125)	(0.136)	(0.141)	(0.201)	(0.217)
Seed^{US}	-0.129	0.317***	0.433*	0.877**	0.505***	0.809***	0.928***	0.665***	0.718***
	(0.281)	(0.121)	(0.257)	(0.367)	(0.117)	(0.127)	(0.131)	(0.184)	(0.199)
$Post^{2010}$	-3.722***	0.201	0.110	0.533	0.256	-0.042	0.039	0.296	0.343
	(0.294)	(0.215)	(0.574)	(0.603)	(0.183)	(0.222)	(0.234)	(0.315)	(0.338)
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Founding-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Chi^2	1496.4	147.5	117.8	119.1	250.0	151.2	184.5	76.7	92.3
N	2,224	3,266	1,927	1,827	3,266	3,266	3,266	3,266	3,266

Panel C: Performance of U.S.- and non-U.S. startups in exposed sectors and *Seed* intensity

Dependent variable:	I(Performance indicators)								
	IPO	Acquisitions			Funds collected				
		All	High stakes	High st.^{ppp}	Follow-on	10 mill.	10 mill.^{ppp}	50 mill.	50 mill.^{ppp}
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)
$SeedRatio$ × Seed^{US}	-0.353	0.001	0.538*	0.367	-0.115	-0.113	-0.191	-0.088	-0.096
	(0.337)	(0.112)	(0.312)	(0.320)	(0.104)	(0.118)	(0.122)	(0.162)	(0.172)
Seed^{US}	-0.150	0.240	-0.359	0.101	0.420*	0.843***	1.035***	0.685**	0.765**
	(0.848)	(0.233)	(0.491)	(0.485)	(0.225)	(0.256)	(0.265)	(0.345)	(0.370)
$SeedRatio$	-0.290	-0.017	0.074	0.361	0.005	0.057	0.092	0.056	0.192
	(0.659)	(0.158)	(0.576)	(0.559)	(0.140)	(0.172)	(0.179)	(0.246)	(0.270)
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Founding-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Chi^2	170.7	94.1	61.8	60.7	148.2	83.3	99.6	36.0	42.9
N	594	1,649	691	691	1,649	1,649	1,649	1,598	1,598

Notes: This table displays regressions estimating Equation (1), using a sample of *Seed*-backed startups from the U.S. and specific non-U.S. countries (i.e., Israel, Great Britain, Germany, France, Sweden, and the Netherlands). The specifications in Panels A and B are similar to the baseline matched-sample regressions in Table 4, only here the state-level fixed effects are replaced with country-level fixed effects. Moreover, the *Seed*-dummy is replaced with the $Seed^{US}$ dummy, which is equal to one for all *Seed*-backed startups headquartered in the U.S., and zero otherwise. Panel C is similar but uses the subsample of startups that operate in sectors subject to the SBJA and with low-capital-intensity as in Panel D of Table IA9 (Appendix). We do not consider IP-related outcomes due to limited data availability. Further, the estimations include two variants of all value-related dependent variables, i.e., high stakes acquisitions and the funding targets of 10 and 50 million USD. The variants with *ppp* refer to purchasing power adjusted values for the non-U.S. startups. Standard errors are clustered at the firm level. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

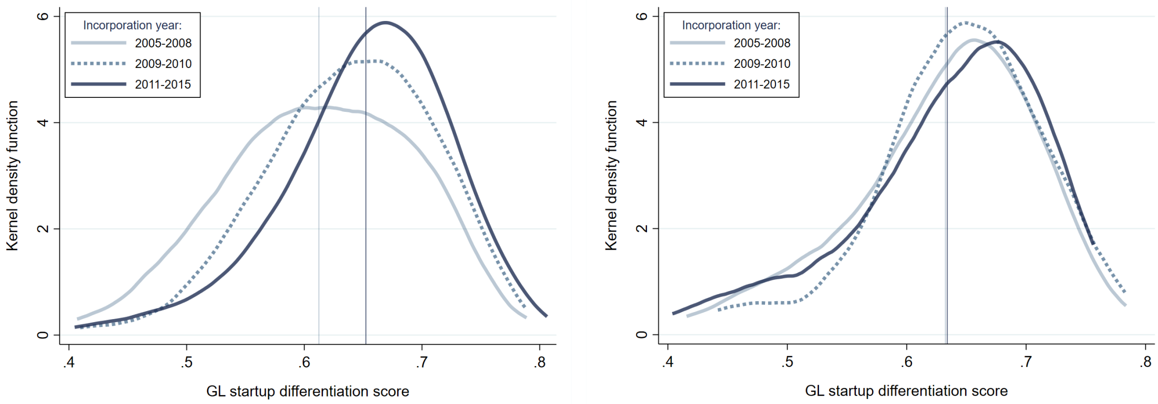
Table IA11: Descriptive statistics on startup founding strategies and the *Seed Boom*

Panel A: Summary statistics on the Guzman-Li differentiation score

	Mean									
	Overall	Pre-2010	Post-2010	Diff. in means	Std. dev.	p10	p50	p90	Min.	Max.
Seed-backed startups	0.642	0.614	0.648	0.034***	0.074	0.54	0.65	0.73	0.30	0.81
Other VC-backed startups	0.632	0.624	0.636	0.012*	0.079	0.52	0.65	0.72	0.32	0.78
Guzman & Li (2023)	0.654	.	.	.	0.064	0.57	0.66	0.73	0.32	0.85

Panel B: Kernel density plot on startup differentiation, matched sample

Seed-backed startups | Comparison group



Notes: Panel A displays summary statistics on the differentiation scores obtained from Guzman and Li (2023), referring to the average distance of the five closest competitors. The displayed values are for initially *Seed*-backed startups, other sample startups, and from Table 2 in Guzman and Li (2023), respectively. Panel B displays the kernel density distributions of the GL-score similar for *Seed*-backed startups and the comparison group firms of VC-backed startups for three time windows: the pre-boom period (2005-2008), the boom period (2009-2010), and the post-boom period (2011-2015). The vertical lines denote the pre- and post-boom average scores.

Table IA12: Assessing differences in startups with and without GL-scores

Panel A: Differential effects of the *Seed* intensity for firms with and without GL-scores

Dependent variable:	I(Performance indicators)								
	IPO	Acquisitions		Funds collected			IP generation		
		All	High stakes	Follow-on	10 million	50 million	Any IP	Patents	Trademarks
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)
SeedRatio × I(GL-score)	-0.004	0.129	0.115	0.035	-0.005	-0.109	-0.112	-0.109	-0.058
	(0.212)	(0.093)	(0.159)	(0.096)	(0.093)	(0.114)	(0.093)	(0.095)	(0.133)
I(GL-score)	0.368	0.037	0.137	0.355*	0.216	0.390*	0.312*	0.268	0.303
	(0.422)	(0.185)	(0.298)	(0.194)	(0.186)	(0.224)	(0.185)	(0.189)	(0.266)
SeedRatio	-0.319	0.008	-0.106	-0.009	-0.076	-0.003	0.085	0.052	0.110
	(0.250)	(0.084)	(0.161)	(0.078)	(0.081)	(0.104)	(0.080)	(0.082)	(0.111)
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Founding-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Chi^2	165.8	163.4	68.9	182.9	225.5	145.2	194.5	236.9	45.1
N	1,954	2,035	1,759	2,035	2,035	2,017	2,035	2,035	2,023

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Table IA12: Robustness tests (*continued*)

Panel B: Differential baseline effects on matched sample regressions from Table 4

Dependent variable:	I(Performance indicators)								
	IPO	Acquisitions		Funds collected			IP generation		
		All	High stakes	Follow-on	10 million	50 million	Any IP	Patents	Trademarks
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)
SeedBoom × Seed × I(GL-score)	0.558	-0.072	0.608*	-0.141	-0.304	-0.282	0.167	0.141	0.210
	(0.461)	(0.201)	(0.348)	(0.208)	(0.204)	(0.238)	(0.201)	(0.205)	(0.282)
SeedBoom × I(GL-score)	-0.143	0.173	-0.156	0.166	0.233	0.093	-0.204	-0.177	-0.202
	(0.340)	(0.167)	(0.242)	(0.172)	(0.167)	(0.188)	(0.165)	(0.168)	(0.220)
Seed × I(GL-score)	-0.778	0.068	-0.919	0.153	0.502	0.404	-0.314	-0.261	-0.258
	(0.863)	(0.392)	(0.612)	(0.405)	(0.395)	(0.461)	(0.390)	(0.397)	(0.550)
SeedBoom × Seed	-0.787**	0.130	-0.634**	-0.199	-0.020	0.025	-0.115	-0.141	0.005
	(0.385)	(0.133)	(0.260)	(0.129)	(0.130)	(0.159)	(0.130)	(0.132)	(0.188)
I(GL-score)	0.637	-0.001	0.609	0.199	-0.145	0.114	0.504	0.414	0.498
	(0.632)	(0.318)	(0.462)	(0.324)	(0.317)	(0.355)	(0.313)	(0.318)	(0.414)
Seed	0.706	-0.245	1.063**	0.340	-0.420	-0.435	-0.094	-0.037	-0.254
	(0.766)	(0.262)	(0.465)	(0.260)	(0.260)	(0.318)	(0.262)	(0.266)	(0.381)
SeedBoom	0.029	-0.063	0.114	0.113	-0.007	0.036	0.186*	0.164	0.130
	(0.312)	(0.115)	(0.189)	(0.109)	(0.109)	(0.137)	(0.110)	(0.112)	(0.143)
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Founding-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Chi^2	200.4	163.4	73.0	187.5	254.7	155.9	205.0	246.4	53.3
N	1,954	2,035	1,759	2,035	2,035	2,017	2,035	2,035	2,023

Panel C: Availability of the GL-score and startup performance

Dependent variable:	I(Performance indicators)								
	IPO	Acquisitions		Funds collected			IP generation		
		All	High stakes	Follow-on	10 million	50 million	Any IP	Patents	Trademarks
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)
I(GL-score)	0.363**	0.279***	0.328***	0.422***	0.205***	0.188**	0.103	0.066	0.195**
	(0.159)	(0.065)	(0.126)	(0.065)	(0.064)	(0.079)	(0.063)	(0.065)	(0.092)
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Founding-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Chi^2	151.6	162.3	61.2	182.5	223.9	142.6	193.9	236.7	43.6
N	1,954	2,035	1,759	2,035	2,035	2,017	2,035	2,035	2,023

Notes: The table presents sensitivity checks, testing the robustness of the main findings on the performance implications of the *Seed Boom* in terms of availability of the GL-score. The regressions include an indicator variable, I(GL-score), that is equal to one for all startups that were successfully linked to the website distance measures provided in Guzman and Li (2023), and zero otherwise. Panel A is equivalent to the specification in Table 4, but uses the I(GL-score) indicator instead of the *Seed* dummy. Panel B is also equivalent to the specification in Table 4, only here the I(GL-score) is interacted with the main regressors in a triple-differences specification. Panel C displays the association between the GL-score and the main startup performance measures, as defined before. Standard errors (in parentheses below coefficients) are clustered on the startup-level. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table IA13: Robustness test on Panel B of Figure 4

Panel A: Alternative differentiation score measures

Dependent variable:	*Startup Differentiation*							
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
$SeedRatio_\tau$ × Seed	0.023**	0.021*			0.022**	0.023**		
	(0.011)	(0.012)			(0.010)	(0.011)		
$SeedRatio_\tau$	-0.004	0.003						
	(0.009)	(0.010)						
$Post_\tau^{2010}$× Seed			0.036**	0.041**			0.027*	0.028*
			(0.015)	(0.018)			(0.006)	(0.006)
$Post_\tau^{2010}$			-0.003	0.006				
			(0.013)	(0.015)				
Seed	-0.027	-0.025	-0.009	-0.015	-0.021	-0.022	0.000	0.001
	(0.018)	(0.022)	(0.011)	(0.014)	(0.006)	(0.006)	(0.006)	(0.006)
Differentiation type:	Avg. distance	Cl. neighbor	Avg. distance	Cl. neighbor	Avg. distance	Cl. neighbor	Avg. distance	Cl. neighbor
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Founding-year FE	No	No	No	No	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.18	0.15	0.19	0.16	0.26	0.24	0.25	0.24
N	650	650	650	650	664	664	664	664

Panel B: Comparing *Seed*-backed and non-*Seed*-backed startups

Dependent variable:	*Startup Differentiation*							
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
$SeedRatio_\tau$	0.017***	0.023***	-0.005	0.000				
	(0.003)	(0.003)	(0.006)	(0.006)				
$Post_\tau^{2010}$					0.030***	0.039***	-0.001	0.007
					(0.005)	(0.006)	(0.007)	(0.009)
Sample:	*Seed*-backed		Matched sample		*Seed*-backed		Matched sample	
Differentiation type:	Avg. distance	Cl. neighbor	Avg. distance	Cl. neighbor	Avg. distance	Cl. neighbor	Avg. distance	Cl. neighbor
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Founding-year FE	No	No	No	No	No	No	No	No
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.11	0.11	0.22	0.18	0.11	0.11	0.22	0.18
N	1,916	1,916	460	460	1,916	1,916	460	460

Notes: This table displays robustness tests to Panel B of Figure 4. In Panel A, Columns I-IV are equivalent to the main specification but do not include founding-year fixed effects, such that none of the individual components of the interaction terms are omitted. Columns V-VIII are also equivalent to the main specification, only here the GL-score on public firms (instead of startups) is applied to measure the distance to startups' closest competitors. Regressions in Panel B display the association between *Seed* intensity (Columns I-IV) and the GL-scores of *Seed*-backed startups (Columns I-II) and startups from the comparison group (Columns III-IV). Columns V-VIII repeat the first four specifications but use the Post-2010 indicator instead of the intensity measure to quantify the *Seed Boom* stages. Standard errors (in parentheses below coefficients) are clustered on the startup-level. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table IA14: Robustness tests on the investment patterns of *Seed* investors

Panel A: Using alternative measures to measure the stage of the *Seed Boom*

Dep. variables:	log(avg. deal size)	log(nbr. deals)	SD deal size	Nbr. co-investors
	(I)	(II)	(III)	(IV)
$Post^{2010}$ × Seed	-0.090**	0.289***	0.068***	0.295***
	(0.044)	(0.039)	(0.020)	(0.083)
Additional controls:				
Investor-level controls	Yes	Yes	Yes	Yes
Investor FE	Yes	Yes	Yes	Yes
State-year FE	Yes	Yes	Yes	Yes
N	16,776	16,776	16,776	16,776
R^2	0.77	0.77	0.60	0.57

Dep. variables:	Local targets	Targets with IP	Experience (startups)	Experience (exits)
	(I)	(II)	(III)	(IV)
$Post^{2010}$ × Seed	0.009	-0.024	0.012	0.028***
	(0.015)	(0.015)	(0.021)	(0.011)
Additional controls:				
Investor-level controls	Yes	Yes	Yes	Yes
Investor FE	Yes	Yes	Yes	Yes
State-year FE	Yes	Yes	Yes	Yes
N	16,776	16,776	12,424	12,424
R^2	0.70	0.53	0.47	0.44

(continued on next page)

Table IA14: Robustness tests (*continued*)

Panel B: Subsample of VCs with *Seed* targets

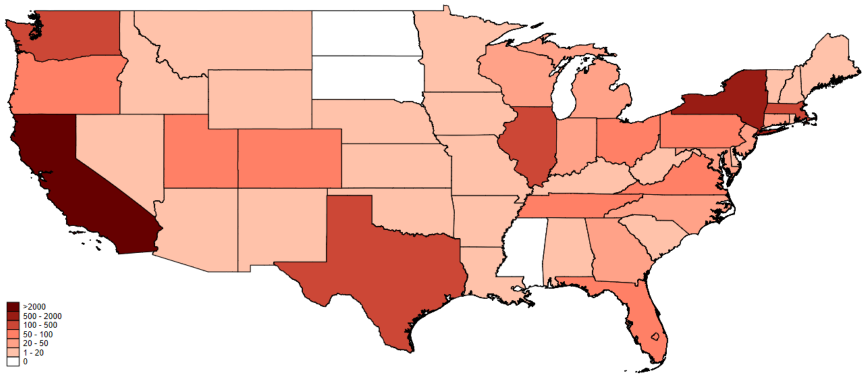
Dep. variables:	log(avg. deal size)	log(nbr. deals)	SD deal size	Nbr. co-investors
	(I)	(II)	(III)	(IV)
SeedRatio	-0.073***	0.129***	0.057**	0.215***
	(0.016)	(0.017)	(0.010)	(0.029)
Additional controls:				
Investor-level controls	Yes	Yes	Yes	Yes
Investor FE	Yes	Yes	Yes	Yes
State-year FE	Yes	Yes	Yes	Yes
R^2	0.77	0.73	0.54	0.51
N	11,150	11,150	11,150	11,150

Dep. variables:	Local targets	Targets with IP	Experience (startups)	Experience (exits)
	(I)	(II)	(III)	(IV)
SeedRatio	-0.013**	-0.016***	0.032***	0.014***
	(0.005)	(0.006)	(0.006)	(0.003)
Additional controls:				
Investor-level controls	Yes	Yes	Yes	Yes
Investor FE	Yes	Yes	Yes	Yes
State-year FE	Yes	Yes	Yes	Yes
R^2	0.66	0.52	0.42	0.38
N	11,150	11,150	9,389	9,389

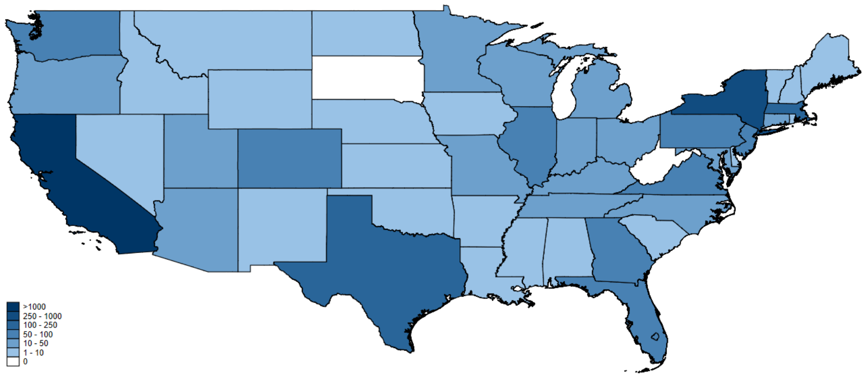
Notes: This table displays robustness tests on regression that explain the relationship between the *Seed Boom* and investment patterns using the investor-year panel described in Section 3.2. The estimation specifications are similar to those in Table 5. In Panel A, the estimates use the $Post^{2010}$ dummy instead of the *Seed* ratio to measure the stage of the *Seed Boom* over time. Panel B repeats these estimations for the subsample of VC investors with a *Seed* target. Standard errors (in parentheses below coefficients) are clustered on the investor-level. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Figure IA1: Geographic locations of first-round equity investment targets, by type

***Seed*–backed targets:**



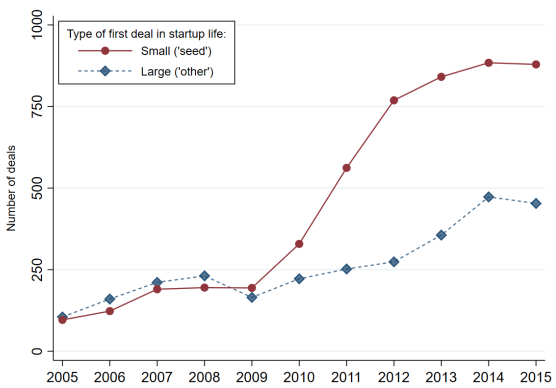
Other first round targets:



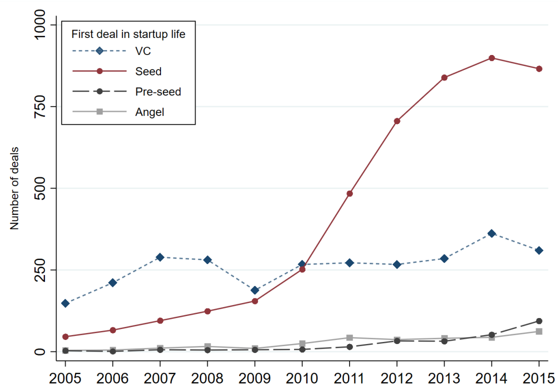
Share among total (in %)	
Location (state):	
California	46.54
New York	17.86
Massachusetts	5.41
Texas	2.84
Washington	2.65
Illinois	2.73
Florida	1.62
Others	20.35

Figure IA2: Different perspectives on early-stage startup financing in the U.S. (2005-2015)

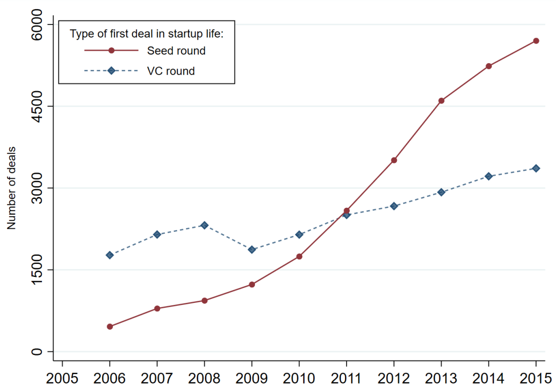
Panel A: Own *Seed* classifications



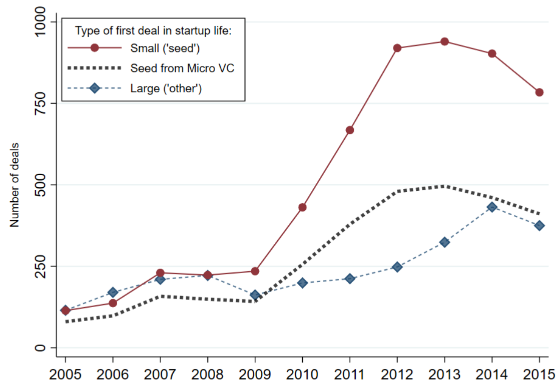
Panel B: Crunchbase investment classifications



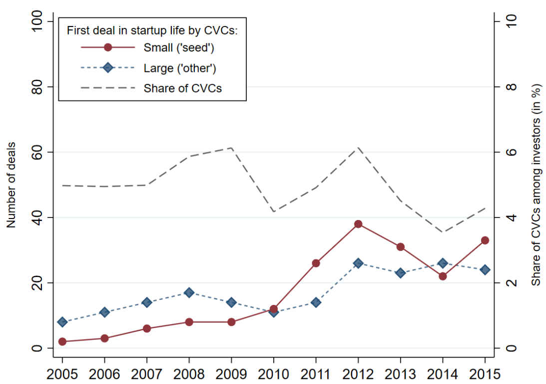
Panel C: Pitchbook data



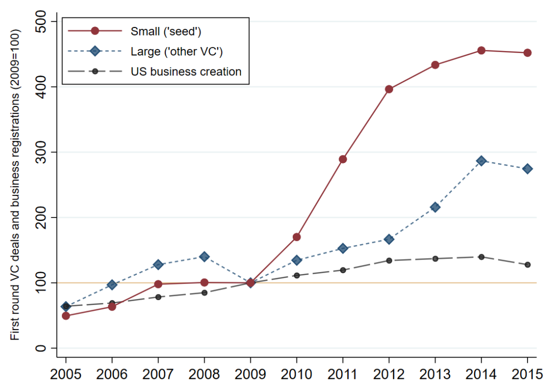
Panel D: Investor type "venture capitalist" only



Panel E: Share of CVC investments



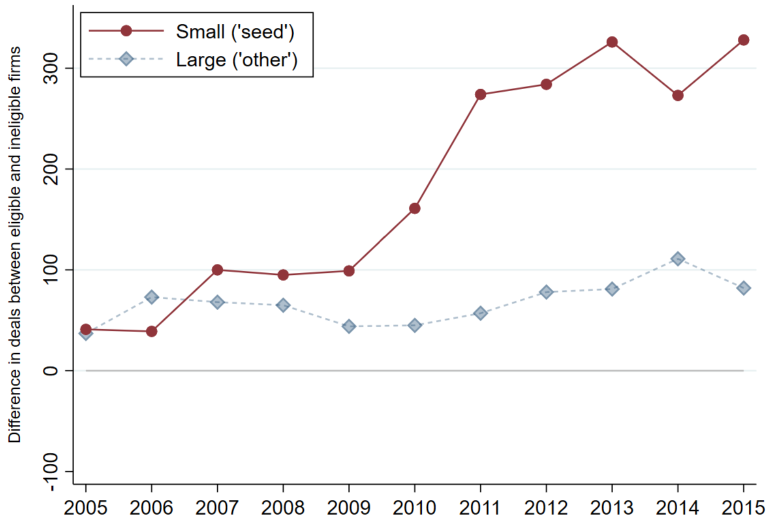
Panel F: Investments and business creation



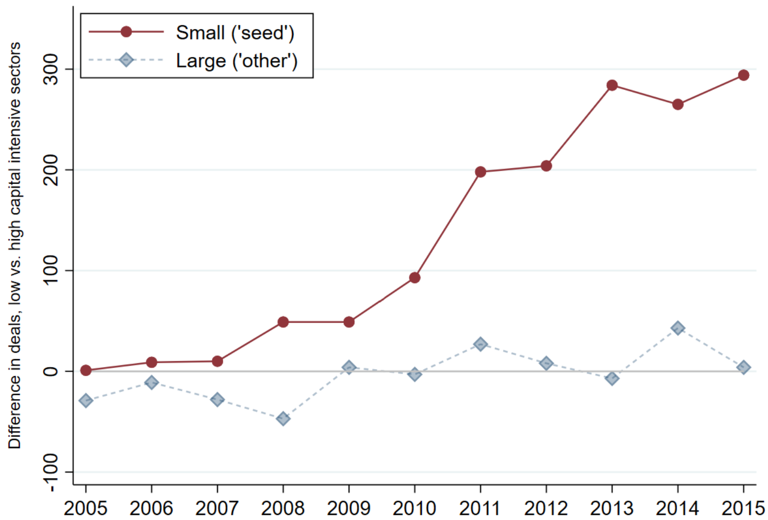
Notes: This figure illustrates the development of early-stage equity financing activities for U.S.-based investment targets in the years 2005-2015. The data is the universe of investment deals listed in the Crunchbase database for startups with a U.S. address, founded in 2002 or later, and with a first investment round between 2005 and 2015. The graph displays the absolute number of first-time financing events per year across different investment type definitions. Panel A follows our main classification approach, as outlined in Section 3.1. *Seed* ("Other") deals refer to any first time external equity investment that is conducted by an investment fund and has a maximum (minimum) deal volume of 2 million USD provided for an investment target with a maximum (minimum) age of 2 years at the time of the investment. In Panel B, the classification of first-round equity investments follows the Crunchbase labels, distinguishing seed, pre-seed, angel, and VC rounds. Panel C uses out-of-sample data from Pitchbook (only available as of 2006) and distinguishes the investment type classes seed and VC. Note that these values do not specifically refer to the first deal but more generally refer to any early-stage rounds. By definition we thus expect slightly higher values in the absolute number of deals relative to the Crunchbase data. Panel D excludes all startups without investors that are labelled as "venture capitalist" or "micro VC" in the Crunchbase data. The dashed line represents the number of Micro VC within this group. Panel E displays the shares of CVC investments within the first rounds observed in our data. Panel F plots the frequency of seed and later-staged deals as in Panel A, only here the values are indexed with 2009 equal to 100 and the graph includes the values of startup creation rates as displayed as in Table 2.

Figure IA3: Robustness test: Factors driving the rise in early-stage startup financing

Panel A: Difference in deals across sectors, comparing targets eligible and ineligible to SBJA tax exemptions



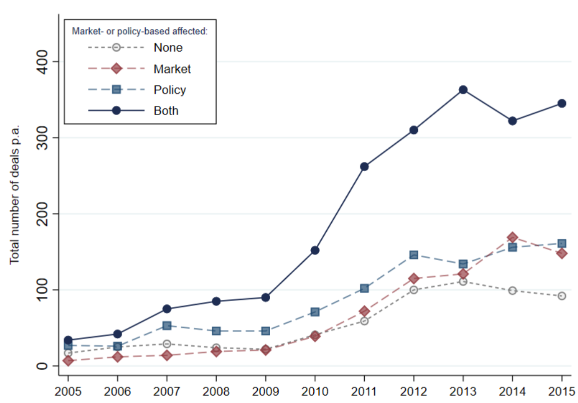
Panel B: Difference in deals across sectors, comparing targets from high- and low-capital-intensive sectors



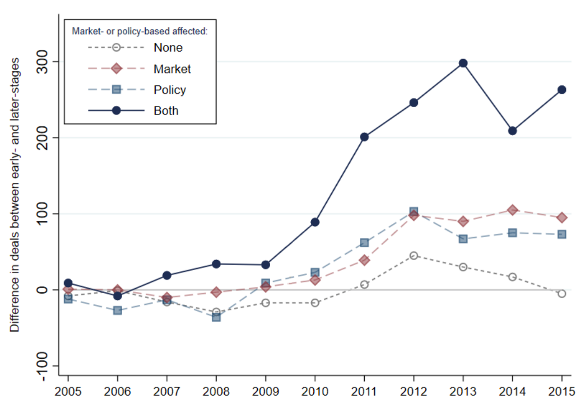
Notes: These figures displays statistics similar to Figure 2, dinstinguishing first-round startup investment patterns of SBJA eligible and non-eligible sectors (Panel A) and high- versus low-capital-intensive sectors (Panel B). Only here, the graphs display the difference in absolute number of rounds between startups in sectors with relatively low capital-intensity and startups in relatively high-capital-intensive sectors within respective cohorts. All numbers are end-of-year total investment counts.

Figure IA4: Simultaneity in the effects of market- and policy-based factors

Panel A: Annual number of deals



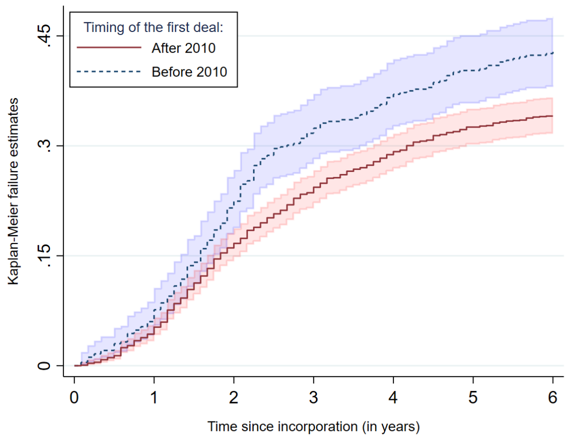
Panel B: Difference in deals across sectors



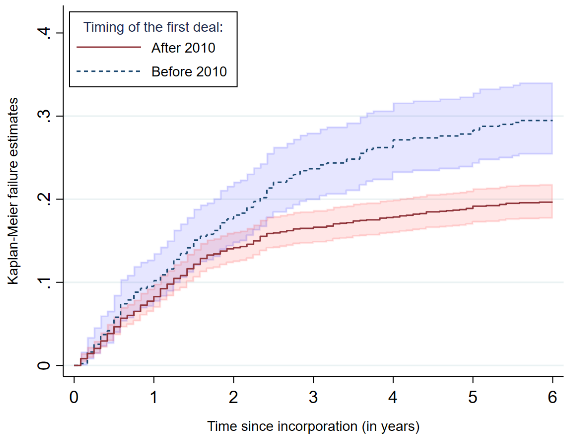
Notes: This graph displays the development of first-round *Seed*-backed U.S. startup investments, distinguishing firms that are subject either to both market- and policy-based factors, to none, or to only one of these factors. The graphs are structured similar to those of Figure 2. Panel A plots the annual number of deals by respective cohorts. Panel B displays the difference in absolute number of rounds between startups startups that are initially *Seed*-backed to those that receive financing at later stages but share the same business field categories. All numbers are end-of-year total investment counts.

Figure IA5: Hazard rates on the probability of generating intellectual property, before and after 2010

Panel A: Patent filings



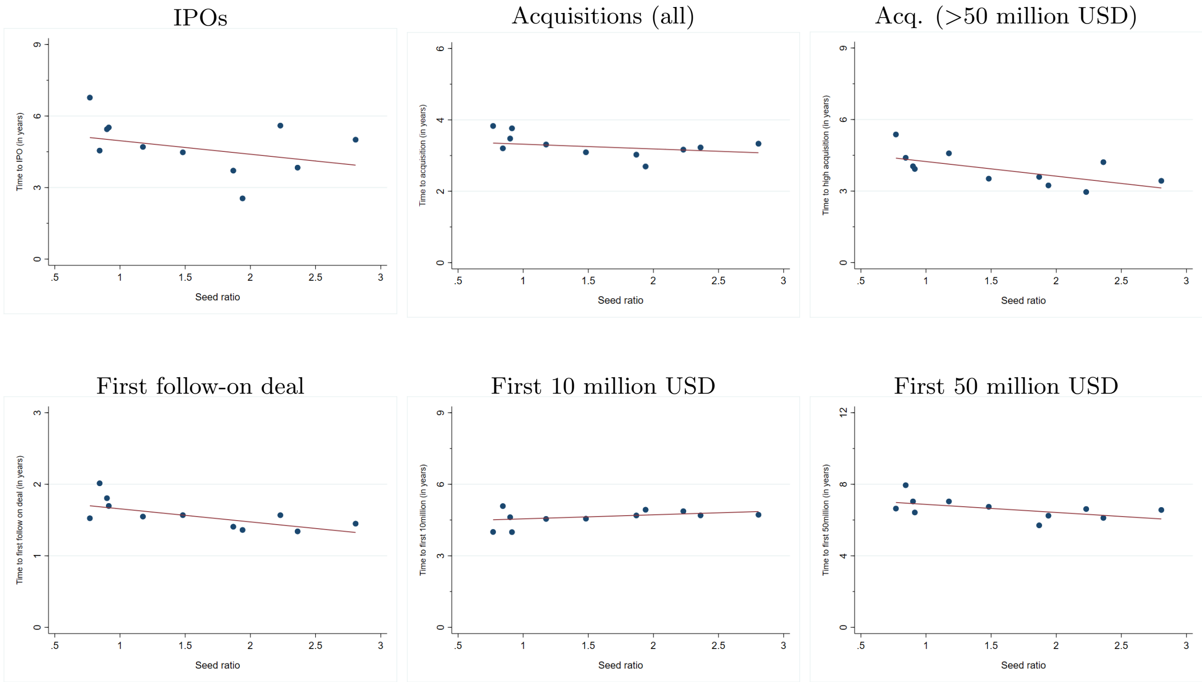
Panel B: Trademark registration



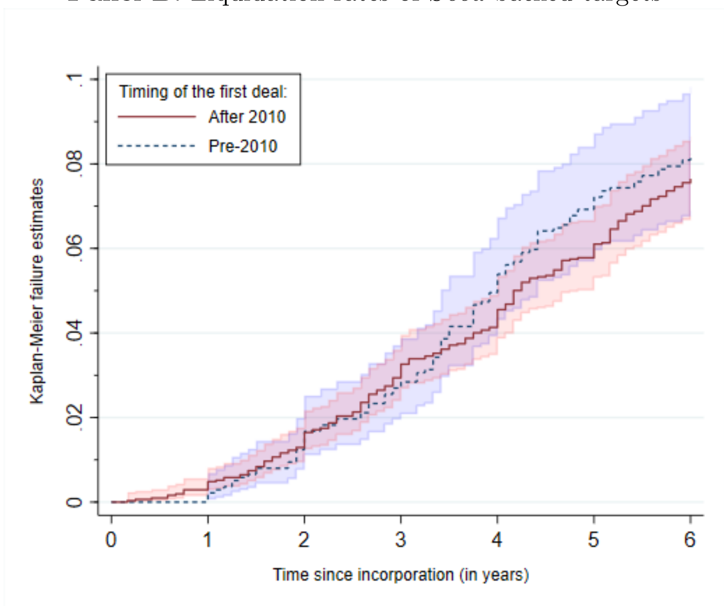
Notes: This graph is similar to Figure 3 and documents the timing of IP generation within the first six years after incorporation, distinguishing *Seed*-backed startups before and after 2010. The two panels display the hazard rate for patent filings and trademark registrations, respectively. The shaded areas around the hazard rates mark the 95% confidence intervals.

Figure IA6: Robustness tests on the performance implications of the *Seed Boom*

Panel A: Scatterplots relating the *Seed*-intensity to performance outcomes

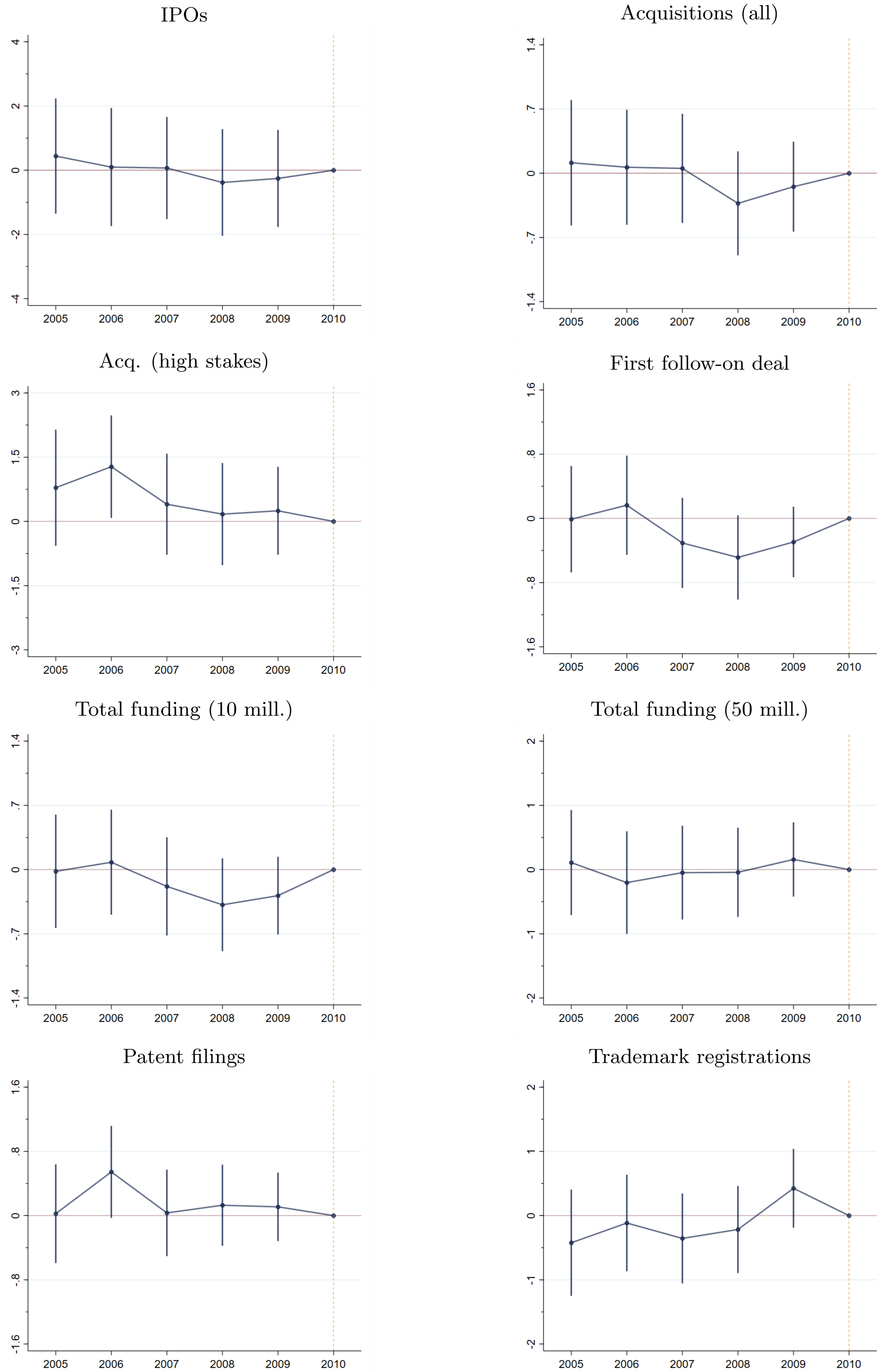


Panel B: Liquidation rates of *Seed*-backed targets



Notes: These figures display robustness tests to the hazard estimations in Figure 3. The graphs in Panel A are binned scatterplots instead of the Kaplan Meier survival estimates, relating the time to having a successful performance event relative to the *Seed*-intensity in the U.S. market. The intensity is measured as the share of *Seed*-backed in the sample relative to all early-stage funded startups, as shown in Table 2. The performance measures remain the same as before. Panel B displays the probability of firm closure within the first six years after incorporation, comparing *Seed*-backed startups that were incorporated before and after 2010, respectively. Closure refers to all startups that are assigned a definite closure date in the Crunchbase data. For consistency, we only consider closures that are not associated with acquisitions. The shaded areas around the hazard rates mark the 95% confidence intervals.

Figure IA7: Testing differential performance trends in the matched sample by funding-year cohort

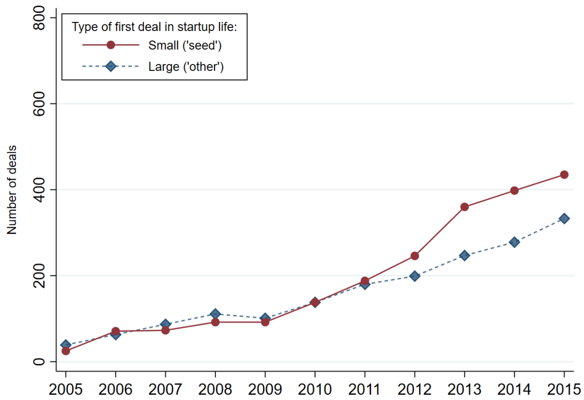


Notes: This figure coefficient plots on regressions that test for differential performance dynamics between *Seed*-backed startups and startups in the comparison group, following the matching process as outlined in Section 4.1. The underlying regression is similar to Equation (1), only here, the sample considers the pre-*Seed-Boom* period. Further, the *SeedRatio* variable is exchanged with a series of dummy variables that are equal to one in each of the funding-year cohorts $\tau \in [2005, 2009]$. Hence, 2010 serves as the reference year. The outcome variables are the different performance indicators, referring to the probability of reaching an IPO, an acquisition, acquisitions with a reported purchasing price of at least 100 million USD, the probability of receiving follow-on investment, a cumulative total amount of 10 or 50 million USD in external equity funding (second row), a patent filing, or a trademark filing. All variables are defined in Table IA2 (Appendix). The whiskers span the 95% confidence intervals.

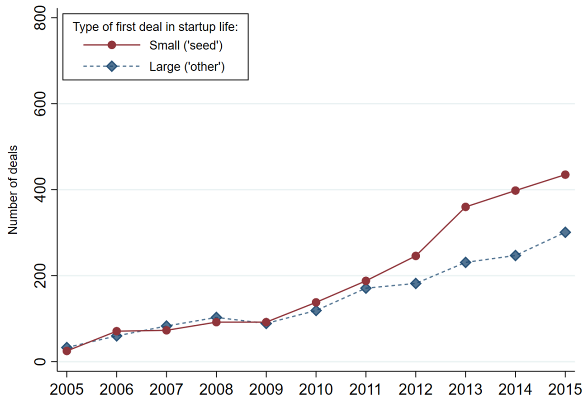
Figure IA8: Startup funding rates outside the U.S.

Panel A: Early-stage equity investments, non-U.S. startups

With PPP adjustment

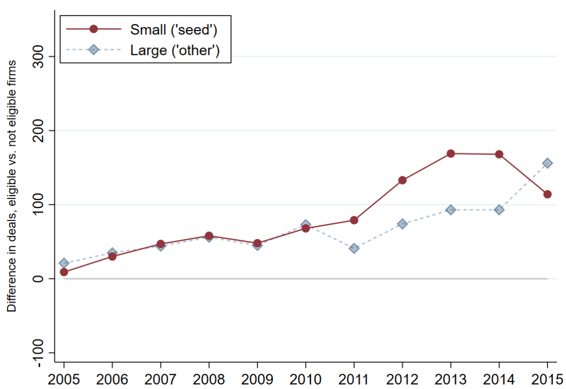


Without PPP adjustment

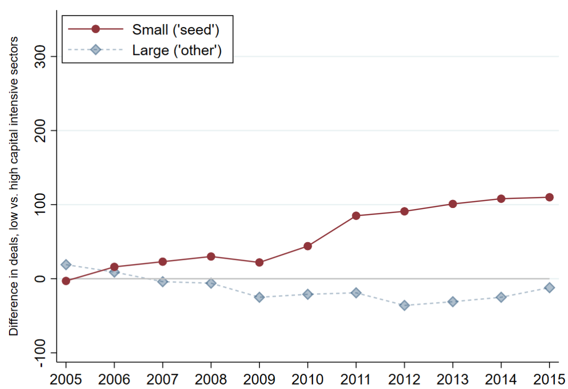


Panel B: Placebo test: Differences in early-stage financing of non-U.S. startups

Sectors eligible to SBJA rule



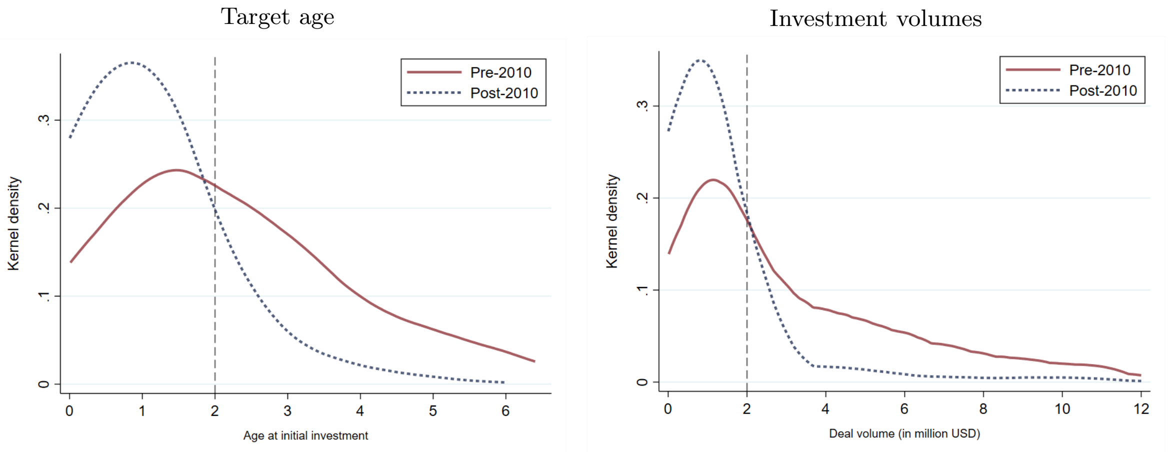
Sectors with low capital intensity



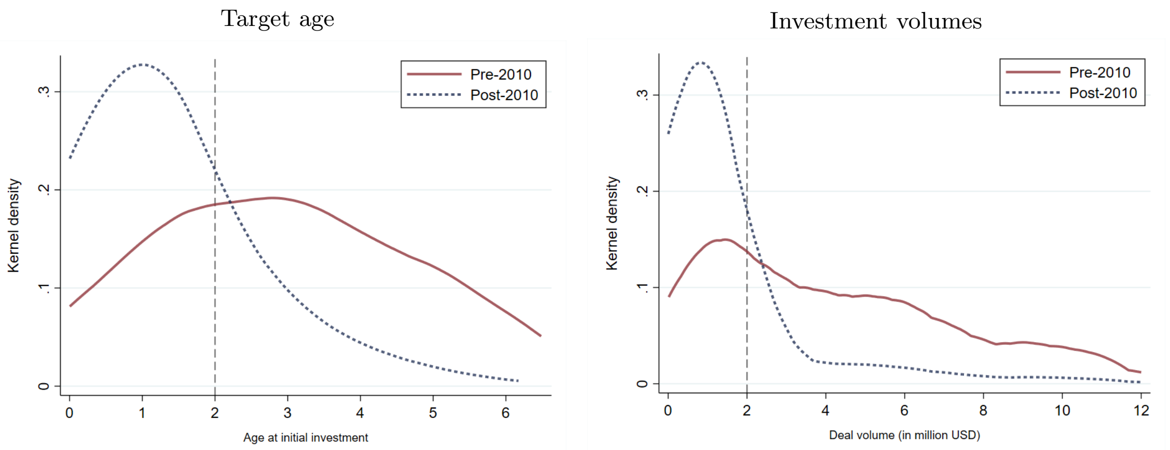
Notes: Panel A displays the development of early-stage equity financing activities for non-U.S.-based startups, similar to Panel A of Figure IA2 (Appendix). Non-U.S. based startups refer to those headquartered in any of the following economies: Israel, Great Britain, Germany, France, Sweden, and the Netherlands. The two graphs use purchasing power parity adjusted (left panel) and non-adjusted (right panel) cutoff thresholds to classify startups as *Seed*-backed. All numbers are end-of-year total investment counts. Panel B recasts the Figure IA3 (Appendix), using the sample of non-U.S.-based startups. It displays the differences in the number of rounds comparing startups in sectors with relatively low and high capital intensities (left graph) and sectors eligible and non-eligible to the SBJA tax exemption (right graph), respectively.

Figure IA9: Age and investment size distributions for startups with and without GL-scores before and after 2010

Panel A: Startups with GL-score



Panel B: Startups *without* GL-score

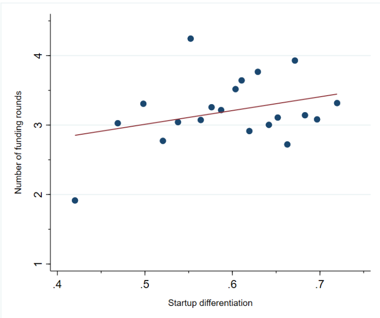


Notes: The figure displays the kernel density distributions of target age and investment size equivalent to Figure 1. Only here, Panel A and B display distributions for all startups with and without a GL-score, respective. For simplicity, the graphs only distinguish between pre- and post-2010 values. All other specifications remain as before.

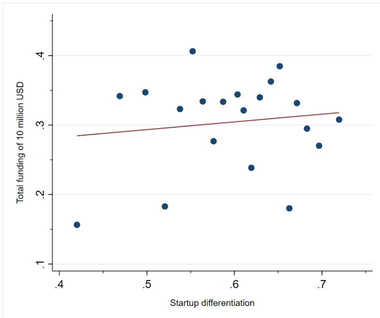
Figure IA10: Startup differentiation at incorporation and performance

Panel A: Funding-related outcomes

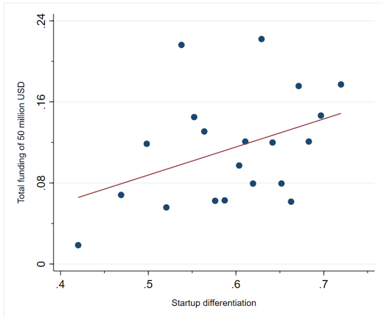
Number of funding rounds



10 million funding

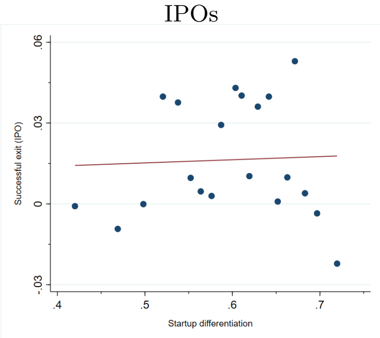


50 million funding

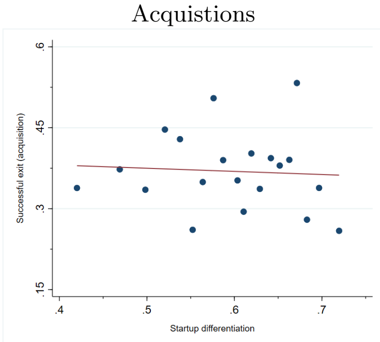


Panel B: Successful exits

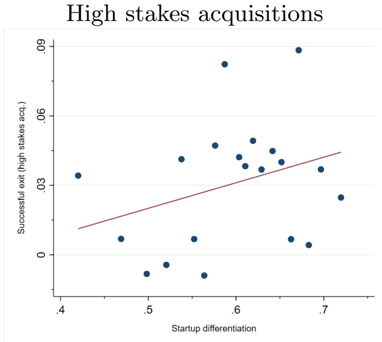
IPOs



Acquistions

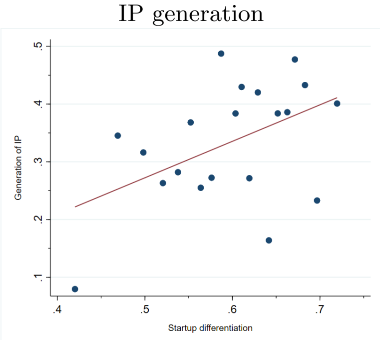


High stakes acquisitions

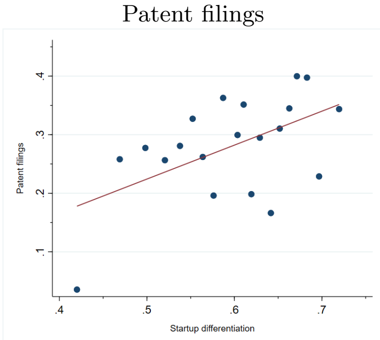


Panel C: Intellectual property outcomes

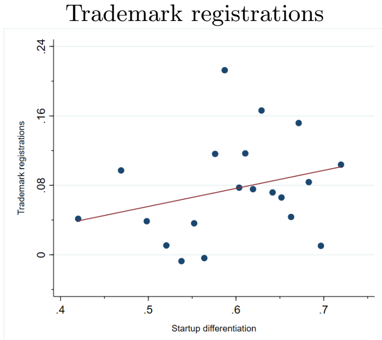
IP generation



Patent filings



Trademark registrations



Notes: The binned scatterplots display the relationships between the levels of startup differentiation upon incorporation and subsequent performance outcomes. Startup differentiation scores are obtained from Guzman and Li (2023); the performance outcomes are defined as before. The bin size is 20 and the red line displays the linear fit.