The Rise of Early-Stage Financing in the US and Startup Performance

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This paper examines startup performance in the context of the *Seed Boom*, a previously unexplored but significant transformation in the US entrepreneurial financing landscape. Unparalleled by other developments, the frequency of first-round VC investments towards particularly young startups quadrupled within three years during the early 2010s, facilitating the survival of promising but high-risk startups. This shift has received little attention in the academic literature, while its potential (negative) implications in terms of a potential crunch in follow-on investments and startup performance were extensively debated by practitioners at the time. Consistent with the resource-based view but contrary to practitioners' concerns, we find that many *Seed*-backed startups were able to secure follow-on investments. Similarly, we provide robust evidence that the *Seed Boom* was not accompanied by a decline in startup performance. As potential mechanisms, we show that *Seed*-backed startups provide unique business opportunities serving as critical resources, which, however, need the complementary resources provided by VCs to unfold their potential.

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1 Introduction

Entrepreneurial startups play a central role in developing new business ideas, thus shaping economic growth (e.g., Haltiwanger *et al.* 2013). Specialized intermediaries, such as venture capitalists (VCs), are essential for these startups' financing activities (Gompers and Lerner 1999; Hellmann and Puri 2002; Chemmanur *et al.* 2011; Lerner and Nanda 2020), which in turn are shaped by the economic environment and public policies (Fairlie and Chatterji 2013; Cumming and Li 2013; Ewens *et al.* 2018). Fueled by new technologies and governmental interventions in the aftermath of the Global Financial Crisis (see Brynjolfsson and Collis 2019; Edwards and Todtenhaupt 2020), the entrepreneurial financing landscape in the US underwent substantial changes during the early 2010s: early-stage startup investments shifted towards ever younger targets and became significantly smaller than in any previous year. For example, the number of investment funds' first-round equity deals with less than two million USD that targeted young startups not older than two years more than quadrupled between 2009 and 2013. This increase is disproportional relative to other VC investments and startup creation rates.

Despite the significance of this shift, surprisingly little is known from the academic literature about the potential consequences of this *Seed Boom*. In contrast, there are widespread debates among practitioners about possible implications. For example, Sam Altman voiced major concerns about the performance implications of this unprecedented surge in low-volume, high-risk equity investments into nascent startups.[1] In this paper, we provide empirical evidence on the performance implications of the rise in early-stage financing around 2010. To this end, we study startups' IPO and acquisition rates, their ability to secure follow-on financing, and their intellectual property activities (patent and trademark filings) in a representative sample of almost 8,000 US-based ventures active between 2005 and 2015. The data covers information on investment histories, firm performance, as well as founder- and investor-level characteristics, allowing us to draw a comprehensive picture of the entrepreneurial financing landscape during the early 2010s.

Studying this change in the US startup financing landscape is important because, a priori, its implications are unclear. The common concern of practitioners at the time was that the surge in early-stage funding favors targets with inherently higher failure rates, potentially setting up a large number of star-

[1] Altman is the former president of the startup accelerator Y Combinator and CEO of OpenAI. In 2014, Altman posted on Twitter that "*seed money is so easy to raise in the current environment that founders assume they can just raise more money whenever they want. [T]his meets cold reality when companies try to raise money again*". He concluded that this would "*mean death*" for many startups.

tups to a severe crunch in subsequent investment rounds and thus in their business development (e.g., The Wall Street Journal 2014). Indeed, very young targets are associated with high information opacity and uncertainty, increasing the risk of investment misallocation. This concern echoes academic literature, arguing that the abundance of financing and, thus, low competition for funds may lead to more startup activity but also to more startup failures (Kerr and Nanda 2009; Hong *et al.* 2020). At the same time, the market- and policy-based changes in the aftermath of the Financial Crisis potentially mitigate the resource constraints of investors, allowing them to pursue investments into specific high-potential targets (e.g., Ewens *et al.* 2018). The increased availability of and access to resources provided by VC funds may thus unleash the potential of *Seed*-backed startups. In line with the resource-based view (Barney 1991; Barney *et al.* 2001), resource availability drives organizations' opportunity recognition. This aspect is particularly crucial in the context of our study, as entrepreneurial firms typically lack the needed resources to develop opportunities. In particular, VC funds provide more than just financial resources that startups lack: As specialized intermediaries, VCs grant their portfolio companies access to their own resources of technological-, market-, and industry knowhow by actively monitoring, governing, or advising startups (Casamatta 2003; Bottazzi *et al.* 2008; Lerner and Nanda 2020).

We find that the *Seed Boom* did not lead to lower startup performance, corroborating the resource-based view in the management and entrepreneurship literature. As such, those young, equity-backed startups that constituted the rise of early-stage funding (henceforth, *Seed*-backed startups) are able to secure follow-on funding and, on average, exhibited comparable or even superior performance compared to other entrepreneurial startups that receive VC financing at later stages. These findings are robust to applying matched sample regressions and controlling for startup-, industry-, and time-specific characteristics. Further, these patterns do not change during the early 2010s. We show that this performance resilience can be attributed to enhanced differentiation strategies of targeted startups as well as diversification strategies of investors. These results suggest that *Seed*-backed startups provide critical resources, i.e., unique business opportunities that serve as a competitive advantage in the spirit of Barney (1991). Still, they require the complementary resources provided by the VC investor to unfold their potential. Our findings thereby emphasize the overall positive implications of the changes in the entrepreneurial finance landscape during the early 2010s, as investors increasingly shifted their investments towards more risky but also more successful startups, lifting resource constraints of these firms. We conceptually underpin these findings, applying the resource-based view in the context of early-stage financing.

Our empirical analysis starts with a notable observation: We show that first-round equity deals from investment funds with a maximum volume of two million USD, targeting US-based startups under two years of age, increased by about 430% between 2009 and 2013. This growth was primarily driven by disproportional investments into targets with less capital-intensive business fields and preferential legislative changes, such as the introduction of the Small Business Jobs Act (SBJA) in 2010, as underlying factors of this *Seed Boom*. Against this background, we examine startup performance in terms of exit rates, firms' ability to obtain follow-on financing, and generation of intellectual property. In contrast to the concern voiced by practitioners, *Seed*-backed startups do not exhibit lower exit, follow-on investment, and IP generation rates, in general. We test these findings along several dimensions, including different variants of matched sample regressions.

As a key result, we find that *Seed*-backed startups do not only perform equally well, compared to other VC-backed startups but that the *Seed Boom* during the early 2010s is also not associated with a decrease in startup performance. To show this, proceed in two separate steps. First, we show that the relative performance of *Seed*-backed startups did not disproportionally change comparing pre- and post-2010 years. If anything, their performance improved relative to other US-based entrepreneurial startups. Corroborating this result, liquidation rates remained constant throughout the early 2010s. Second, we deploy a complementary empirical strategy comparing the performance of early-stage equity-backed US startups with a set of comparable startups from outside the US. As we show, startups in similar markets outside the US were not subject to the same market- and policy-based changes compared to their US peers: There is no equivalent shift towards particularly young first-round investment targets in the seven economies with the most similar VC financing markets outside the US during the early 2010s.[2] Using this setting, we show that early-stage financed US startups' relative performance is comparable with those of their international peers throughout the early 2010s, corroborating our previous results on the performance of *Seed*-backed startups.

Next, we carve out potential mechanisms behind the relatively good performance of high-risk *Seed*-backed startups. As a startup-based mechanism, we show that these startups follow specific differentiation strategies. To do so, we assess startups' founding strategy, utilizing a novel measure of startups'

[2]We acknowledge that US and non-US startups will likely differ along unobservable and institutional characteristics. To partially account for this, we demonstrate that US and non-US startups evolved along parallel paths before 2010.

strategic differentiation at the time of founding adopted from Guzman and Li (2023). The measure captures the distinctiveness of startups' founding strategy and strongly relates to startup performance. We find that *Seed*-backed startups exhibit a higher degree of differentiation from other startup competitors, especially after 2010. This finding corroborates the resource-based view, suggesting that firms' differentiation strategy mirrors specific resources and capabilities controlled by startups that provide them with a competitive advantage. In this context, we document that *Seed*-backed startups typically signal their capabilities through the founding team. In contrast, startups with first-round deals at a later stage and of higher volume are more likely to signal their quality via tangible business outcomes, such as generated innovative output (i.e., patents).

In addition to this, we analyze whether and how investors adopted their investment patterns during the early 2010s as another, investor-based mechanism. Our analyses show that investors did not excessively fund risky targets. Over the course of the early 2010s, syndication rates increased, and investors staged their investments into increasingly smaller tranches, while we find no evidence for increased risk-taking. These insights suggest that investors curb the high risk inherent to nascent targets by applying diversification strategies.

Overall, the analyses reveal insights into a significant yet understudied evolution in the US startup financing landscape. Despite the higher risk associated with nascent firms, the shift towards *Seed* investments fostered the development of profitable startups. The findings enhance the understanding of different startup investment patterns and, thus, the entrepreneurial process as a whole. Notably, the results emphasize the workings of the early-stage entrepreneurial finance sector and their potential to foster startup success by providing critical resources in dynamic market environments.

This paper contributes to the rich literature on startup financing that investigates the effect of VC financing on firm performance. A large body of research ascertains superior firm outcomes of VC-backed firms in terms of higher probabilities of survival, going public or being acquired (e.g., Hellmann and Puri 2000; Cockburn and MacGarvie 2009; Chemmanur *et al.* 2011; Puri and Zarutskie 2012), engaging in strategic alliances and technology licensing (Hsu 2006; Ozmel *et al.* 2013), and generating innovation (Kortum and Lerner 2000; Samila and Sorenson 2011; Howell *et al.* 2020). Rin *et al.* (2013) and Lerner and Nanda (2020) provide comprehensive overviews on these topics. Our analyses offer new evidence on the importance of necessary resources to startup success in a previously undisclosed setting and by examining startup performance under changing market conditions.

Compared to the extensive research on VC financing, literature on other modes of early-stage financing is scarce (e.g., Tenca *et al.* 2018), especially regarding the first-time equity investments of nascent startups. Some studies demonstrate the enhancing effect of accelerator groups and programs on startup performance (Gonzalez-Uribe and Leatherbee 2018; Cohen *et al.* 2019; Hallen *et al.* 2020; Yu 2020). A few studies, such as Kerr *et al.* (2014), investigate angel financing, typically provided by wealthy individuals or specialized organizations, and conclude that it positively impacts startup performance. Hellmann *et al.* (2021) discover that investor-led angel- and company-led VC financing are dynamic substitutes while formerly considered sequentially operating (i.e., complementary) intermediaries. Our work focuses on company-led external equity financing and differentiates among investment types. A group of related studies compares VC-backed startups to those backed by other forms of early-stage funding and documents mixed results: Goldfarb *et al.* (2013) find no difference in the performance of angel investment targets and VC targets, while Amore *et al.* (2022) find traditional VCs outperform micro VCs. These contrasting results illustrate the difficulty of predicting the relative performance of startups and, thus, the implications of shifts in the startup financing landscape. Unlike the studies mentioned above, we examine the performance of initially *Seed*-backed startups relative to comparable US-based startups that receive VC funding at later stages or comparable non-US startups that were not subject to the changes in the financing environment. Overall, our paper sheds light on a substantial market development in the US during the early 2010s. It thereby adds to our understanding of changes in the entrepreneurial financing landscape, their implications for startup performance, and the adjustment mechanisms of the key parties involved.

2 Theoretical considerations

According to Barney (1991), all imperfectly imitable and non-substitutable tangible and intangible assets controlled by a firm are considered value-relevant resources. The generation and maintenance of such resources are particularly crucial for entrepreneurial firms. As such, established companies often already accumulated significant amounts of resources and have the market power to negotiate the terms of acquiring resources once they experience resource scarcity (see Zahra 2021). By definition, entrepreneurial activities involve the (re-)combination of existing resources to create new, unique, and sometimes even disruptive capabilities that cannot be substituted by larger companies, providing startups with potential strategic advantages (Alvarez and Barney 2001). At times, startups are even able to transform their business fields, shaping the generation and orchestration of resources in respective fields (e.g., Radjou *et al.* 2012) or even create entirely new fields. However, in contrast to more mature firms, entrepreneurial startups often control fewer resources and, thus, are dependent on the capabilities owned by other market participants in order to access a broader range of missing assets (e.g., Kor and Mahoney 2005; Nason *et al.* 2019). Aggravating this issue, startups carry the burden of newness and smallness, and often, their founders lack experience in managing existing resources (Brinckmann *et al.* 2011).

Given their lack of resources, startups must focus on assembling resources to enable growth and, thereby, overcome the liabilities of newness and smallness. In particular, new startups are often constrained in financial and human capital: Lacking availability of funds or adequate personal are the typically cited problems faced by young firms (e.g., Cooper *et al.* 1994; Gilbert *et al.* 2006). While the impact of financial resources in enabling the development and eventually the commercialization of products or services, the lack of human capital entails more complex consequences. Most fundamentally, startups require specific expertise and highly skilled workers, especially during the early phases of the lifecycle (Ko and McKelvie 2018). In addition, however, necessary resources often missing in startups are general organizational capabilities, such as operational knowledge and experience, strategy development, or industry networks (Newey and Zahra 2009; Nahata 2019).

VCs have emerged as specialized financial intermediaries that provide financial and organizational resources. Literature has established that VC investors grant their portfolio companies access to their own resources of technological-, market-, and industry knowhow by actively monitoring, governing, or advising startups (Casamatta 2003; Bottazzi *et al.* 2008; Lerner and Nanda 2020). For example, they take an active role in the human capital of a firm by not only advising but also appointing key personnel (Kaplan *et al.* 2009; Ewens and Marx 2018). Hence, although VCs are likely not entirely removing startups' financial and organizational resource constraints, they lift this burden in a significant manner.

The transformation in the entrepreneurial financing landscape during the early 2010s represents a significant shift in the availability of the resources provided by VC investors. While practitioners expressed concerns about the potential negative effects of the abundance of easy-to-access funding, the theoretical considerations outlined above suggest that the increase in early-stage funding might have helped to provide necessary resources for entrepreneurial firms to grow. Therefore, investigating the implications of this *Seed Boom* is essentially an empirical task that we address in our analysis.

3 Definitions, data, and descriptive statistics

3.1 Classifying early-stage investments

There is no universally applicable definition that clearly delineates the different types of early-stage equity investments, such as pre-seed, seed, or Series A deals. Consequently, databases commonly used in the entrepreneurial finance literature typically use overlapping definitions.[3] However, providing an unambiguous definition of early-stage investments is essential for our analysis.

We base our classification of early-stage investments on two genuinely applicable aspects: i) these investments occur at very early stages of the startup life, and ii) they involve comparably small volumes. To define specific thresholds, we consider the median investment volume and target age of first-round equity deals in the US during 2005 and 2006 (i.e., our first sample years). This definition corresponds to all first-round equity investments by private funds with a maximum deal volume of two million USD targeted at firms within the first two years after incorporation as early-stage investments. We collectively refer to early-stage equity investments as *Seed* investments, reflecting that the vast majority of the respective deals are labeled as *Seed* investments in the Crunchbase data (see Table IA1 in Appendix). Unlike this label, our definition allows for a clean delineation of relatively early and relatively late first-round equity investments. Further, our measure also allows us to better assess changes in deal characteristics since other classification patterns may vary over time.

We focus on equity investments by professional VC investment funds. Such funds have the prime objective of generating returns on behalf of their capital providers and fulfill several roles by selecting and actively managing a portfolio of innovation-intensive startups to maximize these returns (Hellmann and Puri 2002; Bottazzi *et al.* 2008). Investments into entirely new startups involve relatively small deal sizes, and target firms typically do not have an existing track record. Hence, at this early stage, the investor's role in providing resources that are missing to entrepreneurial startups is particularly crucial.

[3] For example, Crunchbase distinguishes the following overlapping categories, all of which refer to an early-stage equity investment: 1) Pre-seed and angel rounds involve relatively small financing volumes (i.e., below 150,000 USD) and typically do not involve investment funds. 2) Seed rounds are larger than the pre-seed or angel deals and range between 0.1 and 2 million USD. 3) Early-stage VC rounds range on average between 1 and 30 million USD (Series A and B) or include later-stage investments in more established companies, usually with a minimum investment of 10 million USD.

Such resources include but are not limited to financial dimensions. Often, they comprise organizational capabilities that support the transformation process of product conceptualization to commercialization by providing a combination of active management, monitoring, and advice (see Figure IA1, Appendix). Moreover, focusing on VC funds mitigates the effect of confounding factors that arise from differences in investment strategies associated with other early-stage equity investor types, such as angels investors or incubators (e.g., Block *et al.* 2019; Gompers *et al.* 2020).

3.2 Data and summary statistics

The startup and investor characteristics information is obtained from Crunchbase.com, listed as of February 2023. Startup-level data comprises information on the firm, individual funding rounds, founder characteristics, and various performance indicators. The initial sample covers all startups with a registered address in the US and that received a first-round equity investment by a private investment fund. We follow related literature (e.g., Edwards and Todtenhaupt 2020) and focus on startups that obtained their first financing round between 2005 and 2015, excluding firms founded before January 1, 2000.[4] We complement this data with information about startups' patenting and trademark filings. The patent data combines the Patent Examination Research Dataset (PatEx) from the United States Patent and Trademark (USPTO) and more granular quality measures obtained from the worldwide patent statistical database PATSTAT. Overall, 34.4% of investment targets file at least one patent, comprising 83,776 individual applications. Further, we add startup-level trademark data obtained from the USPTO Trademark Case Files Dataset, using the probabilistic record linkage method (Hall *et al.* 2001). Table IA2 (Appendix) lists all key variables used throughout the analyses. Our sample contains information on 7,964 individual startups and 24,346 individual funding rounds.

In general, the startups in our sample are small, very young, and tech-oriented ventures. By definition, however, compared to other first-round equity targets, *Seed*-backed targets are younger when receiving the first investment (0.77 versus 3.49 years) and obtain smaller sizes deals (0.75 versus 6.07 million USD). Panel A of Table 1 shows that startups are predominantly located in large states typically associated with innovation clusters, such as California, New York, and Massachusetts. This pattern is consistent across startup types (see Figure IA2, Appendix). Furthermore, most *Seed*-backed startups operate in

[4] Specifically, we condition on external equity investments conducted by investors labeled as "organizations", which comprises mainly investors labeled as "venture capitalist" or "micro VC" (see Panel B of Table IA1, Appendix). Section 3.2 shows that the investment patterns are robust to excluding startups with investors from any other category.

software, internet services, mobile, and data analytics. Again, these fields are similar to those of other equity-backed startups. Notably, however, the distribution within these sectors varies substantially (see Table IA3 in the Appendix). As such, *Seed*-backed startups are less likely to operate in capital-intensive sectors, such as hardware, science and engineering, healthcare, biotechnology, or manufacturing.

- Insert Table 1 here -

As main dependent variables, we deploy three distinct dimensions of startup performance. First, we use data on the timing and accumulated amount of external equity financing collected by startups as indicators of a successful performance. Second, we assess whether startups eventually have a successful exit, i.e., either by having an initial public offering (IPO) or by being acquired. Third, we consider the creation of IP, such as patents or trademarks, as a performance dimension. Examining IP filings as a 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; Hsu and Ziedonis 2013; Howell *et al.* 2020). Moreover, using the raised funding volumes and generated IP as performance measures is helpful as these activities are found to serve well as substitute measures for exits once a sample contains young startups that are too young for an exit (Yimfor and Garfinkel 2023). To account for the censoring of the data, we measure these performance outcomes within the first eight years after incorporation and only consider startups that were incorporated by 2014. Panel B of Table 1 provides statistics on these performance dimensions of sampled startups.

3.3 Institutional setting: The boom of early-stage financing

Annecdotal evidence: The startup investment environment underwent significant changes in the aftermath of the Financial Crisis of 2008 and 2009. One particular development was that initial equity investments shifted towards targeting ever younger startups with smaller deal volumes. This trend was widely discussed in the startup finance community. For example, Peter Wagner, a top tech investor of Wing Venture Capital, reports on the surge in the number of early-stage equity-funded startups in the US throughout the 2010s. According to Wing Venture Capital (2021), seed deals gained a new role in serving as a prime mode of first-round equity investment, building the foundation of a company. In contrast, traditional VCs increasingly fund more mature firms based on financial metrics, such as annual earning reports. Other insiders, such as Josh Kopelman (2015), a partner at First Round Capital and an early-stage venture capitalist, state that it has become much easier and takes much less time for an entrepreneur to raise a first round in the early 2010s.

The implications of this shift in early-stage financing have still not been investigated. Practitioners state that easy-to-receive first-round funding may create a wrong perception to many entrepreneurs regarding the chances of obtaining subsequent funding (Kopelman 2015). With more startups receiving low-stake first-round deals, chances for the average startup to obtain follow-on investments are likely to decrease due to higher competition – a situation which Kopelman (2015) refers to as "Series A Crunch".

Descriptive evidence: We confirm this anecdotal evidence, applying the definition of *Seed* investments from Section 3.1. Table 2 shows the rapid increase of smaller first-round investments targeted at younger startups with smaller deal volumes from 2005-2015. By definition, before the Financial Crisis, first-round investments of institutional investors with a maximum size of two million USD targeted at startups not older than two years were equally frequent as larger first-round equity investments targeted at more mature startups. As of 2010, the number of first-round equity investments surged. Importantly, this change is predominantly driven by a disproportional rise in *Seed* rounds. In 2012, *Seed* deals were 2.8 times more frequent than larger deals targeted at older startups.[5] This development is unrelated to underlying business formation changes. As such, the increase in *Seed* investments exceeds the rate of startup creation in the US over the same time frame (Column "*Startup creation*" in Table 2). While 1.7% of newly created US firms received *Seed* investments in 2009, the ratio increased to 4.9% in 2012. Panel E of Figure IA3 (Appendix) presents this result graphically. For robustness, Panel B of Table 2 illustrates the shift in the timing and volumes of first-round investments in more detail. The graphs display the distributions of target age and investment volumes of first-round equity deals in the US. Along both dimensions, there is a significant shift comparing deals before and after 2010.

- Insert Table 2 here -

Additionally, descriptive statistics also support the practitioners' notion of a potential "Series A Crunch". Specifically, the last column in Table 2 Panel A reports the share of first-round *Seed*-backed startups that eventually obtained an equity deal of at least two million USD. The share of initially

[5]To mitigate concerns that this pattern arises from selection criteria of Crunchbase, the definition of specific classification thresholds, or compositional shifts, Figure IA3 (Appendix) displays different variants of the same timeline and shows that using Crunchbase or Pitchbook classifications for seed investments and excluding startups whose investors are not explicitly labeled as "venture capitalist" or "micro VC" leads to similar evolutions (Panels A-C). Panel D shows that the observed pattern is not driven by a compositional shift related to changes in the prevalence of corporate venture capitalists.

Seed-backed startups with such subsequent deals declined from about 50% in 2008-2010 to about 35% five years later. Since the time lag between initial and subsequent deals is typically less than two or three years, right censoring is unlikely to cause this result. Hence, the likelihood of *Seed*-backed startups notably decreases over time, which is consistent with the practitioners' concerns.

Underlying factors: Several complementary factors are likely to have triggered the rise of *Seed* financing during the early 2010s. Indeed, such significant transformations are unlikely to have a singular cause. In the following, we outline two essential developments that contributed to the shift, i.e., market and policy-based factors. Notwithstanding, there are likely further aspects that spurred this development.[6] Providing an exhaustive list of factors or detailing the question about the relative importance of the described factors goes beyond the scope of our analysis. Still, these examples show how changes in market conditions affect the resources available to investors that are then utilized to fund and manage young startups.

As a first dimension, we show that the emergence of low-capital-intensive startups is a critical market-based factor related to the increase of early-stage startup investments. Since the early 2000s, the US economy evolved towards a more digital marketplace at an accelerated pace (e.g., Brynjolfsson and Collis 2019; Tambe *et al.* 2020). The Financial Times (2020) coined the 2010s as "*The FAANG Decade*", referring to the disproportional growth of the tech sector in the 2010s.[7] Digital business strategies rely more on intangible assets that require less upfront capital investments. Hence, it seems reasonable that the digital transformation ultimately altered the amount (and timing) of funding required to start a business throughout the 2000s.

To test this link, we examine the composition of business fields of *Seed*-backed startups. Specifically, we gather the main business fields of the so-called FAANG companies from Crunchbase, namely, software, data, internet, cloud, platforms, apps, security, and payment – all of which are low capital intensive. We then collect all subfields related to these main business activities, as listed in Table IA5 (Appendix). Using this definition, we find that the pattern observed in Figure 1 can be mostly attributed to an inflow of firms operating in these sectors. Panel A of Figure 2 displays the absolute number of first-round

[6] For example, the post-crisis years mark an attractive financing environment due to abundant cheap money available for startup financing (see Lerner and Nanda 2020). As such, various financing platforms were launched, making it easier for professionals and individual angel investors to participate in early-stage financing activities both formally and informally (Cohen *et al.* 2019; Hallen *et al.* 2020). These factors are relevant for new investors and incumbents, such as established VCs, which often pursue strategic investments to fend off entry (Hochberg *et al.* 2010).

[7] The acronym stands for the five US tech companies: Facebook, Amazon, Apple, Netflix, and Google.

investment deals, similar to before, but distinguishes firms from sectors with relatively low and high capital intensities. While the relative incidence of *Seed* deals across the different business fields prior to 2010 is comparable, low capital intensity sectors disproportionally attract more early and low-volume first-round deals beginning in 2010. Importantly, these patterns do not reflect a general trend of increased investments into sectors with low capital intensity. To illustrate, Panel A of Figure 2 also displays the absolute difference in first-round investments comparing low and high capital-intensive sectors for both *Seed* deals and other first-round equity deals. Overall, these statistics suggest that compositional changes in the business fields towards low capital-intensive sectors are one factor contributing to the shift in first-round equity investments in the US.

- Insert Figure 2 here -

As a second dimension, policy-based factors are a complementary stimulus to market-based transformations. To exemplify the role of policies for the *Seed Boom*, we relate the rise of early-stage startup financing to the 2010 *Small Business Jobs Act* (SBJA). The SBJA was a key policy change in the US that rendered investments into early-stage startups more attractive by providing potential investors with a tax exemption on realized profits.[8]

Exploring this setting, we find that the SBJA can be associated with the shift towards increased *Seed* investments in the US during the 2010s. To do so, we use the eligibility criteria to single out startups subject to the SBJA. Panel B of Figure 2 distinguishes startups in sectors eligible for tax exemption and those that are not. Indeed, eligible startups account for most of *Seed* deals after 2010. Confirming this, we also find that the spread in *Seed* deals between startups eligible and ineligible for SBJA tax exemption sharply widens as of 2010. The rate of relatively larger first-round equity investments is fairly stable, irrespective of the business activities. These results demonstrate that changes in the law are also likely to have contributed to the transformation in the entrepreneurial financing landscape in the US during the early 2010s.[9]

[8]The implementation of the SBJA allowed investors a full exemption from federal taxation of capital gains realized on the sale of the shares of certain qualified startups that were obtained after September 27, 2010. For an excellent assessment of the SBJA for startup financing, we refer to Edwards and Todtenhaupt (2020).

[9]In fact, the rise of early-stage startup financing during the early 2010s is predominantly driven by startups that are subject to both factors simultaneously (see Figure IA4, Appendix). This insight highlights the complementary importance of market forces and policy initiatives to foster dynamics in the marketplace.

4 Performance of early-stage backed startups

4.1 Basline assessment: startups' success probabilities over time

Hazard estimates: To analyze startup performance, we start by estimating the probability of a successful startup performance outcome to arrive over time. To this end, we assess the timing of startup performance using Kaplan-Meier failure estimates ("hazard rates") and distinguish startups that initially receive *Seed* financing and those receiving their first round at a more mature stage (denoted as "Others"). We reshape the data to a startup-month panel, which measures months relative to the incorporation date of the startup. To indicate successful performance events, we use dummy variables equal to one in the week the startup reaches any respective performance event and zero otherwise.

First, we assess the rate of successful exits through IPOs or acquisitions. Overall, sampled startups account for 2,527 exits (2,359 acquisitions and 178 IPOs) for startups in our sample. Panel A of Figure 3 shows that 26% of initially *Seed*-backed startups exit via an acquisition within the first eight years. Acquisitions involving *Seed*-backed startups occur significantly earlier than those of other equity-backed targets for which the probability of being acquired is significantly lower (18%). However, conditional on a relatively high acquisition price, i.e., of at least 50 million USD, the difference in acquisition rates becomes much smaller (see Panel B). Hence, *Seed*-backed startups are acquired more often and at earlier stages of their life cycle compared with other VC-funded startups, but low-stake acquisitions predominantly drive this difference. Assessing IPO rates mirrors these findings (see Panel C). The likelihood of *Seed*-backed startups going public within the first eight years after incorporation is only about 1.1%. This number is significantly lower than for startups that obtain the first round at a more mature age (1.9%), but the differences in economic terms are arguably low.[10]

- Insert Figure 3 here -

Next, we investigate startups' ability to secure follow-on funding. *Seed*-backed firms have about a 60% chance of obtaining subsequent funding within the first five years after receiving the first investment. Most of these startups receive the second round within the first two years. For comparison, only 51% of other equity-backed startups receive a second financing round. The differences in the timing and the probability of receiving a subsequent deal most likely reflect that funding volumes of initial *Seed* deals

[10]For complementary statistics on acquisition and IPO rates, see Panel A of Table IA6 (Appendix).

are relatively small, and thus funds are depleted relatively fast. Corroborating this view, the pattern changes when we condition on receiving subsequent funding rounds with a minimum deal volume of two million USD. In this case, 41% and 44% of initially *Seed*-backed and other startups receive subsequent equity deals within five years after the initial funding round (see Panel D of Figure 3). This difference is only weakly significant at the ten percent level. Similarly, the probability of gathering sizable amounts of funding over the long run is comparable across startups. While *Seed*-backed startups are significantly less likely to collect 10 million USD over the long-term, this difference vanishes when considering larger amounts, such as 50 million USD (see Panels E and F of Figure 3). Despite a generally lower share of *Seed*-backed startups with follow-on investments (as shown in Section 3.3), there is no robust evidence that these startups collect fewer funds over a long-term horizon compared to other startups. These results suggest that *Seed*-backed startups can frequently attract follow-on investments. This finding contrasts the concerns expressed by practitioners and suggests that these startups are not disproportionally prone to a funding crunch.

As a third performance indicator, we asses startups' IP filings over time, using data on patent filings and trademark registrations. Overall, 28% of initially *Seed*-backed startups and 39% of other equity-backed startups have filed or registered an IP right by the fifth year after incorporation. Yet, there is no statistically significant difference in IP generation across startups within the first two years after incorporation, i.e., coinciding with the threshold used for defining *Seed*-backed startups. To illustrate, Figure IA4 (Appendix) shows that the probability of a *Seed*-backed startup to file a patent within the first five years after incorporation is significantly lower (22%) than of other equity-backed startups (28%). This difference only emerges *after* the initial two years of incorporation and, thus, may reflect that VC-backed startups use IP rights as a quality signal, as documented in the literature (Hsu and Ziedonis 2013; Haeussler *et al.* 2014). These patterns also apply along several alternative quality-weighted patenting measures (see Figure IA4).

Probit estimates: The hazard estimates on the timing of startup performance showed that *Seed*-backed startups do not generally underperform equity-backed startups. Arguably, however, the observed patterns may be driven by systematic differences between *Seed*-backed startups and those that receive initial equity investment at later lifecycle stages. To demonstrate the robustness of the above findings, we augment the previous analysis by controlling for observable confounding factors using probit regressions.

Specifically, we construct a matched sample that imposes startups (i.e., *Seed*-backed startups versus other startups with equity funding at later stages) to share several characteristics that are already observable at the time the startup is founded. Startups have to share the same founding month, state, and business field. Additionally, we impose startups to feature similar characteristics related to their founders' experience as entrepreneurs, such as previous founding activities and investor age. The matched sample excludes initially *Seed*-backed startups that do not have any comparable partner, yielding a matched sample of 2,041 startups: 1,148 of them are initially *Seed*-backed, and 893 startups are in the comparison group. This approach accounts for important features such that the differences between the two groups are unlikely to arise due to time-, industry-, and founder-specific characteristics.[11]

As a first step, we deploy this matched sample and estimate conditional probit regressions that use the above-described performance measures as dependent variables. Additionally, we control for further time-variant and -invariant observables, such that the differences between the two groups are unlikely to arise due to time-, industry-, and founder-specific characteristics. Formally, we estimate different variants of the following specification:

$$P_i = \beta_t + \beta_j + \beta(Seed_i) + \gamma X_{it} + u_{it} \ , \tag{1}$$

where P_i are different performance outcomes. Investment-year fixed effects (β_t) capture time-specific developments throughout the sample period. Further, industry fixed-effects (β_j) control for the fact that firm performance varies across different fields of business operations. X_{it} is a vector of time-variant controls, including founder characteristics of startups. The dummy variable $Seed_i$ is equal to one if a startup is initially backed by *Seed* investments. Hence, the coefficient of interest is β, which indicates the probability of reaching a given performance goal (P_i) for *Seed*-backed startups relative to initially other equity-backed startups. Standard errors are clustered at the startup level. Panel A of Table IA7 (Appendix) displays the corresponding estimates. The results mirror the findings from the hazard estimates, suggesting that observed performance patterns are unlikely driven by time-, industry-, or founder-specific characteristics.

In addition to this, we use the above setting to address another potential bias. By definition, *all*

[11]Notwithstanding, controlling for these characteristics does not provide us with two identical groups of firms. Instead, this approach serves as the basis to account for the most important observable differences across firms. We approximate the founder's age by the time gap between their first university degree and the date of incorporation of the respective startup.

startups that obtain their initial investments from VC funds at later stages have survived the critical first two years after incorporation. In an alternative approach, we thus account for the fact that non-*Seed*-backed startups entail a survivorship bias by focussing on those eventually reaching a subsequent financing stage. This approach screens out the early-failed startups, which should be less similar to the comparison group startups. In total, this applies to about 43% of initially *Seed*-backed startups.

First, we estimate Equation (1) using the original sample but exclude *Seed*-backed startups without follow-on financing. This approach yields significantly different results compared to before. As displayed in Panel B of Table IA7, conditional on reaching the subsequent financing stage and controlling for observable startup characteristics, the coefficients on the *Seed*-dummy are positive across all performance indicators. However, the coefficients are insignificant for the IPO, high acquisition, and IP generation performance measures. Still, these estimates contrast those of the average *Seed*-backed startup (Figure 3), suggesting that *Seed*-backed startups are likely to outperform the comparison group conditional on reaching subsequent financing. Second, we repeat the analysis using the matched sample as in Panel B. Here, the estimates are similar though less precisely estimated (see Panel C Table IA7 (Appendix). Overall, the results in this section provide a consistent picture showing that, on average, the *Seed*-backed startups cannot be associated with inferior performance compared to other equity-backed startups.

4.2 Testing performance implications of the *Seed Boom*

4.2.1 Comparing pre- and post-Boom startup performance within the US

While the previous section shows that *Seed*-backed startups do not underperform, per se, this section tests whether the *Seed Boom* during the early 2010s was accompanied by a decline in startup performance in terms of successful exits and follow-on investments. We start by analyzing performance differences across time using the matched sample introduced in the previous section. More specifically, we estimate Equation (1) but add an indicator, $Post^{2010}$, and its interaction with the *Seed*-dummy. Hence, a negative coefficient on this interaction term indicates declining startup performance of *Seed*-backed targets comparing pre- and post-Boom funded startups.

Panel A of Table 3 displays the main coefficients. The positive coefficients on the *Seed*-indicator confirm the previous results. More importantly, there are two main observations. First, the coefficients of the interaction terms are small and insignificant for estimates of the probability of IPOs and acquisitions (see Columns I and II). Only the probability of high-stake acquisitions decreases, but the estimate is only weakly significant at the ten percent level (Column III). These estimates imply that the superior performance of initially *Seed*-backed startups over other startups applies before and after the surge in early-stage financing, with only minor variation across time. Second, the coefficients of the interaction terms are sizable and highly significant for estimates of the probability of raising five or ten million USD. With increasing funding size, however, the disproportional positive effect vanishes (see Columns IV–VI in Panel A). For robustness, we confirm these findings using split sample regressions (see Table IA8, Appendix), which also indicate no changes in the probability of generating IP over time. Overall, these findings certainly do not reflect a decrease in the relative performance of *Seed*-backed startups. If anything, these startups have become more successful than the control group in securing investments.

- Insert Table 3 here -

As an alternative approach to assess the implications of the *Seed Boom* on startup performance, we investigate failure rates of *Seed*-backed startups before and after 2010 and show that they do not change over time. To this end, we estimate hazard rates on the likelihood of startup liquidation after incorporation. Liquidation rates are a particularly crucial indicator of startup failure because liquidation often implies that investors write off their entire investment. Overall, 27% of startups in the sample are liquidated by early 2023, i.e., the latest available update of the Crunchbase data used in this study. Although failure rates in observational data are prone to be underreported, this value aligns with other reports on respective liquidation rates. For example, Gage (2012) reported that 30-40% of US venture-backed startups failed between 2000 and 2010. Our sample comprises startups backed by professional VC funds, which may be reflected in the slightly lower liquidation rates.[12] Panel B of Table 3 shows that failure rates of*Seed*-backed startups within the first years after incorporation do not significantly differ comparing pre- and post-2010 levels.

4.2.2 Using non-US VC-backed startups as natural controls

Previous results compare startups within the US that are different by definition. To better understand the implications of startup financing on performance, we compare US-based startups to a similar set

[12]Moreover, in our case, failure rates are in part lower by construction as we impose on firms to survive until the first funding round. We acknowledge that failure can be measured differently, e.g., using negative return on investment (see, e.g., Arora *et al.* 2021). Unfortunately, we cannot identify this with our observational data.

of startups. In particular, we compare *Seed*-backed startups from the US to similar startups *outside* the US, namely, from the seven OECD economies with the largest VC markets: Israel, Canada, Great Britain, Germany, France, Sweden, and the Netherlands.[13]

First, we demonstrate that these economies did not witness a comparable *Seed Boom* around 2010. A priori, it is not clear whether this shift is specific to the US. While some underlying market- and policy-based factors may be US-specific, the entrepreneurial finance landscape is international, with many investors operating across countries. Similarly, the rise of low capital-intensive startups may have been similar outside the US. To illustrate that the developments in the US were unparalleled in the largest non-US markets for startup financing, Figure 4 recasts previous statistics for startups headquartered in any of the comparison group countries. Panel A displays the total number of early-stage startup financing deals and any other first-round equity investments equivalent to Figure 1.[14] Unlike their American peers, there is no disproportional increase in funding of *Seed*-backed targets outside the US. Arguably, we observe a slight divergence indicating a moderately larger increase in early startup financing beginning as of 2012, but this is certainly not comparable to the increase in the US. To illustrate, in 2012, the ratio of initial *Seed* investments relative to other initial deals was 2.8 in the US but only 1.3 in the seven most comparable VC markets outside the US. This absence of a comparable shift in the entrepreneurial financing landscape outside the US is consistent with the observation that, for example, European countries suffered from VC investment shortfalls during the 2010s (Cumming and Groh 2018).

- Insert Figure 4 here -

Given these descriptive findings, using non-US startups as a comparison group seems promising for analyzing the changes in the performance of *Seed*-backed startups from the US after 2010. The idea behind this is that one should observe a disproportional decrease in the performance of US-based startups *relative* to non-US startups after 2010, for example, if the increased investment activities are associated with poorer diligence in VCs' selection and mentoring process. We exploit this setting by using difference-in-difference estimations to compare the performance of US-based startups that receive

[13] Aggregate statistics show that these economies have the most similar (albeit not equivalent) VC markets compared to the US, e.g., concerning the size of the VC sector (see OECD Statistical Warehouse, 2010 figures of the tables: "*Venture capital investments*" in current USD prices, development stage "*Startup and other early stage*"). Despite their size, we do not consider China and Japan as they have structurally distinct VC markets (see, e.g., Chen 2022).

[14] The classification of early- and late-initial stage financing are analogous to those used for the US market. In our main specification, however, we adjust the thresholds referring to the two million USD using the purchasing power adjustments to each country. In Figure IA6 (Appendix), we show that the patterns are very similar when not making these adjustments or excluding specific non-EU countries, i.e., Canada and Great Britain.

equity financing at very early stages to similar startups headquartered in large VC markets outside the US ("comparison group") both before and after 2010. Importantly, this strategy does not suggest that US and non-US startups are similar, which they are likely not. Instead, the strategy merely requires that US and non-US startups would have evolved along parallel paths both before 2010 and in the absence of market- and policy-based changes in the US financing landscape. Formally, we estimate:

$$P_i = \delta(Seed_i^{US} \times Post_{it}^{2010}) + \delta_t + \delta_s + \delta_c + \epsilon_{ist} \ , \tag{2}$$

where P_{it} is the performance outcome of firm i that received the first equity financing round in year t. $Seed_i^{US}$ is an indicator equal to one for any startups headquartered in the US and zero otherwise. $Post_{it}^{2010}$ is an indicator equal to one if startup i received its initial VC financing round after 2010 and zero otherwise. The interaction of the two indicator variables estimates δ, i.e., the coefficient of interest, which captures the differential change in performance of early-stage equity-backed startups in the US after 2010 relative to the comparison group. Further, we control for general macroeconomic trends and country-specific differences by including home-country and investment-year fixed effects. The inclusion of these two-way fixed-effects omits the estimates of the base variables $Seed_i^{US}$ and $Post_{it}^{2010}$.

Equation 2 is estimated using repeated cross-sectional data on the sample of startups headquartered in the US or any of the seven economies specified above. Just as before, this includes startups that received initial early-stage financing from an equity fund between 2005 and 2015. Further, sampled non-US startups also received their initial deal within the first two years after incorporation and obtained a total financing volume of less than two million USD at purchasing power parity. Finally, the main analyses in this section focus on startups that comprised the *Seed Boom*, i.e., startups active in business fields subject to market- and policy-based factors. This approach results in a sample of 3,389 initially *Seed*-backed startups from the US (2,359) and abroad (1,030).

Table 4 displays the results from estimating Equation 2 using different performance indicators as dependent variables. In Columns I-III, probit estimations use a set of dummy variables indicating whether respective startups have successfully exited within the first eight years after incorporation. The insignificant coefficients in Columns I and III suggest no statistically disproportional change in the probability of successful exits when comparing US and non-US-based startups before and after 2010.

The coefficient on IPOs is positive and significant at the ten percent level, indicating that the relative likelihood of an IPO has mildly increased for US-based startups with initial financing at very early stages. In Columns IV and V, the relative probability of raising 10 or 50 million USD has not changed either. We confirm this in an OLS regression (Column VI), which is set up like Equation (2) but uses a continuous dependent variable that counts all funds raised within the first eight years after incorporation.

- Insert Table 4 here -

For robustness, we deploy an addition test in which we examine the dynamic treatment effects using an event study type specification similar to Equation 2. As the dependent variable, we use an indicator of exit, an indicator of high-value exit (i.e., IPOs or acquisitions worth more than 50 million USD), or a continuous variable on the funds collected within the first five years after incorporation. The results displayed in Panel B of Table 4 yield two main takeaways. First, the coefficients in the years before 2010 are insignificant across specifications. This finding supports our approach, suggesting that US and non-US-based startups evolved in parallel trends before 2010. Second, consistent with the results from Panel A, the insignificant coefficients after 2010 indicate that the *Seed Boom* in the US is not accompanied by a decrease in relative performance to international peers. These results are robust to analyzing startups affected by market- or policy-related factors separately (see Table IA9, Appendix), using a triple-DID design, or limiting the comparison to the economies with the most comparable VC markets among the comparison group, i.e., Canada, Great Britain, and Israel (untabulated). Overall, using non-US startups as a comparison group provides additional evidence in line with the previous findings. Again, these results emphasize that the surge in *Seed*-backed startups in the US is not accompanied by a reduction in startup performance, mitigating concerns that the specific selection of the empirical design determines previous results.

5 *Seed*-backed startup performance: potential mechanisms

This section assesses potential mechanisms that better help to understand the previous results. It carves out startup- and investor-based mechanisms why the *Seed Boom* during the early 2010s did not lead to a crunch in follow-on funding and, even worse, in deteriorating startup performance. Specifically, we examine how startups and investors adopted their business strategies as of 2010.

5.1 Startup differentiation strategies

We start by analyzing whether early-stage equity-backed startups' differentiation strategies changed over time. The idea is that more differentiated startups are better equipped to survive in a competitive marketplace in the spirit of an escape competition effect. To investigate this relationship, we utilize a novel measure of startups' strategic differentiation adopted from Guzman and Li (2023). The score quantifies the differences in the value propositions stated on startups' websites at the time of startup creation relative to the propositions of their closest competitors. Competitors can be either startups or public firms. Conceptually, the score captures the uniqueness of startups' founding strategy, which is shown to raise startup performance significantly (see Guzman and Li 2023). We can retrieve the corresponding differentiation scores for 2,548 of the startups in our sample. Panel A of Table 5 displays respective scores and shows that they closely map the scores from the original sample used in Guzman and Li (2023). It also shows that the average differentiation score of *Seed*-backed targets increases comparing pre- and post-2010 levels.

- Insert Table 5 here -

We conduct a series of regressions in which we assess changes in the startup founding strategy of *Seed*-backed targets over time more systematically. Specifically, we reestimate several variants of Equation 1 and use as the dependent variable the differentiation score capturing the distance to the closest cohort startups. Table 5 presents the corresponding results. The specification in Column I regresses a set of founder-level characteristics and industry-fixed effects on the differentiation score using the subsample of initially *Seed*-backed startups. The variable of interest is $Post^{2010}$, a dummy variable equal to one for all startups with an initial financing round in 2010. The positive and highly significant coefficient indicates that startups with early-stage equity funding from VC funds after 2010 are more different compared to their startup rivals and those funded before 2010. Taking the difference between the upper and lower decile score of the differentiation measure, the size of the coefficient suggests that the average *Seed*-backed startup is 15% less similar when we compare before and after 2010.

Furthermore, we add several details to this observation. First, using the full sample of startups, estimates in Column II suggest that, on average, differentiation scores of *Seed*-backed startups and other startups with first-stage financing from VC funds are comparable. The coefficient on the *Seed*-dummy is small and statistically insignificant. Second, reestimating the second specification but including an interaction term $Seed \times Post^{2010}$ shows that the change towards higher differentiation scores after 2010 is predominantly driven by initially *Seed*-backed startups and less so by other VC-backed startups. Finally, we confirm the latter result, including investment-year fixed effects (Column IV), using *Seed*-backed startups with follow-on investments only (Column V), and using the differentiation score relative to public firms (Column VI) as robustness tests.

Moreover, Table IA10 (Appendix) displays the prevalence of quality signals on founders' managerial capabilities. It shows that *Seed*-backed targets feature more visible signals regarding the founding team but fewer tangible signals regarding business activities than startups that receive their first round at a relatively higher age. First, we consider prior entrepreneurial experience to resemble an observable, credible signal about startup quality. The founding teams of *Seed*-backed targets more frequently have prior experience launching a startup (28.2%) compared to relatively older equity-backed startups (15.6%). Similarly, 6.4% of founders of initially *Seed*-backed startups had a successful exit (IPO or acquisition), while this applies to only 4.1% of founders of startups with relatively later first rounds. These differences apply despite relatively similar average founder age. Second, *Seed*-backed startups are less likely to feature tangible signals relating to their business activity at the initial investment. As such, 9.1% of these startups hold a patent before the initial investment round, compared to 33.1% of other early-stage equity-backed startups. These statistics suggest that investors disproportionally select startups based on the available quality signals about their organizational resources. In the case of very early-stage investments, such signals are less likely related to generated output but rather constitute features readily observable upon the startup's inception. These statistics generally emphasize the ability of startups that eventually obtain *Seed* funding to generate critical resources, even at very early stages of the lifecycle.

Overall, the estimates show that *Seed*-backed startups exhibit a higher degree of differentiation from other startup competitors, in particular after 2010. As higher differentiation indicates a higher future performance, these results provide a possible explanation of why startup performance remained constant or even increased despite more risky startups being funded: Targeted startups might have been superior in terms of their differentiation strategy.

5.2 Changes in investment patterns of early-stage equity investors

Next, we examine changes in investors funding patterns over time as a complementary mechanism for the resilience of *Seed*-backed startup performance throughout the changing financing environment of the early 2010s. In this context, we aim to point out whether and how investors adjusted their investment behavior during the *Seed Boom*. In particular, we analyze if investors adjusted their financing patterns by focusing on the risk-taking behavior of investors. The idea is that *Seed*-backed targets are fairly opaque and thus exert a relatively high degree of uncertainty, suggesting that an increase in investments into these targets may reflect excessive risk-taking. A priori, however, it is not clear whether this conclusion applies. With increasing demand and a conducive investment environment at the time, early-stage investments likely became viable for an increasing number of investors, and including very young startups in the portfolio may serve the purpose of diversification.

As a first step, we outline some fundamental investor characteristics, comparing *Seed*-backed startups to relatively late ("Other") first-round equity investments (see Table IA10, Appendix). About half of *Seed* deals (54%) are syndicated deals involving more than one investor, which is higher than for non-*Seed* equity deals (44%). In both cases investors are typically domestic (82% and 81% respectively), but the share of investors located in the same state is higher for startups with earlier first rounds (52%) compared to other startups (41%). Overall, the share of corporate venture capitalists (CVC) among the first-round investors in our sample is fairly small. However, in relative terms, the CVC share is almost twice as high for firms with "Other" first-round equity investments (7%) compared to*Seed*-backed firms (4%). Moreover, investment funds that provide *Seed* investments are younger than non-*Seed* investment funds, with an average age of about 8 and 13 years, respectively. Despite these age differences, investment funds' experience as measured in terms of the Crunchbase rank is very similar, comparing the *Seed*-backed startups to others.[15]

In principle, it is plausible that investors increase risk-taking not only concerning the targets selected (i.e., increasing *Seed* funding) but also regarding the investment process as a whole. Consistent with this, literature documents increased risk-taking of market participants once they face financial slack (e.g., Nanda and Rhodes-Kropf 2017; Almeida *et al.* 2021). Financing of informationally opaque targets could

[15]The rank variable is generated by Crunchbase using proprietary algorithms to rank firms according to their importance. Importance refers to the number of connections of a profile within the platform, including news articles, funding events, and acquisitions. The algorithms allow each of these connections to decay over time, meaning ranks vary over time and are not solely a function of investor age.

thus be the expression of an overall "*spray and pray*" investment strategy, in which investors provide small funding amounts and limited governance to a larger number of startups (Ewens *et al.* 2018). At the same time, it would be equally plausible that investors apply strategies to offset at least parts of the increased risk associated with young targets.

We follow the literature and use a set of different measures for increased and decreased risk-taking to operationalize such investment patterns (listed in Table IA2 in the Appendix as *Investor-level outcomes*). First, the average distance of investors to their targets is an indicator of risk-taking. Investors are aware that farther distances imply lower monitoring; thus, more distant investment targets correspond with higher risk (see Tian 2011; Bernstein *et al.* 2016). We measure distance by comparing whether investors and targets are headquartered in the same state. Second, ex-ante differences across startup founders in terms of experience and age are found to relate to more risky targets (Ewens *et al.* 2018, Azoulay *et al.* 2020). Hence, we quantify the average experience of the founder regarding prior founding activities and age. Third, the share of targets holding IP rights at the time of investment relates to its riskiness as these rights are tangible signals valued by investors (e.g., Hsu and Ziedonis 2013; Haeussler *et al.* 2014). Fourth, staging investments in a higher number of individual deals resembles a form of staging strategy described in the literature (Gompers 1995; Tian 2011). Therefore, we measure changes in investors' diversification strategy using the total number of investment deals per year. As an alternative measure of diversification, we use the average number of co-investors per deal. As such, the syndication of investments is a fundamental strategy to lower their risk exposure.

To analyze investment pattern changes during the early 2010s, we construct an investor-level dataset sampling all US-based organizations that acted as first-round equity investors during 2009-2015 in the Crunchbase data. We apply the same methodology to delineate investments into *Seed* investments and other, larger early-stage equity deals as before. Formally, we estimate the following equation:

$$Y_{it} = \gamma_{st} + \gamma_i + \delta_1 \, Trend_t \times Seed_i^{Investor} + \gamma X_{it} + \epsilon_i, \tag{3}$$

where we use the above-described investment characteristics of investor i in period t, Y_{it}, as dependent variables. $Trend_t$ is a running count of the years (2009-2015), capturing the time trend in the outcome variable. $Seed_i^{Investor}$ is a dummy equal to one for investors that are observed to participate in any *Seed* deal as defined in Section 3.1 and zero otherwise. We include the interaction of the two variables

$(Trend_t \times Seed_i^{Investor})$ such that δ_1 captures any differential change in trends after 2009, comparing *Seed* investors to other investor types. All specifications control for time-varying investor characteristics (X_{it}), which are the six variables specified above, excluding the one used as a dependent variable in the respective estimations and the base values of the interaction term. All regressions control for investor (γ_i) and state-year (γ_{st}) fixed-effects. We cluster standard errors at the investor level.

Estimates in Table 6 support the notion that the patterns of early-stage equity investors did not change towards more risk-taking. Instead, the results point towards risk-mitigation patterns. Panel A displays the estimates for Equation 3. Columns I-IV display coefficients on estimations using the four variables associated with increased risk-taking as dependent variables. Across specifications, the coefficient of interest is small and statistically not significant. In contrast, the two coefficients on the diversification measures are sizable and statistically significant at the one percent level. More specifically, the positive and highly significant coefficients in Columns V and VI indicate that investors engage in more deals while increasing the number of co-investors.

- Insert Table 6 here -

Panel B of Table 6 confirms this notion. The graph plots individual year coefficients obtained from event-study-type regressions using 2009 as the reference year. For the risk-taking measures, coefficients are similar over the observed period, indicating a sideways trend. In contrast, we find a trend toward an increased number of deals per year and more syndicated deals for the two diversification motive measures. While the mere shift towards earlier financing rounds in itself may resemble increased risk-taking, these results provide robust evidence that investors did not adjust investment towards riskier targets altogether. Indeed, investors intensified diversification strategies, potentially to moderate the risk associated with increasingly young targets. In combination with the findings in Section 5.1, these results show that *Seed*-backed startups can offer critical resources in the form of differentiated business strategies, but the complementary resources provided by the VC investor are needed to unleash the potential of these resources.

6 Conclusion

Access to funding is a key determinant for startup success, such that structural changes in their financing environment may have important implications for shaping the trajectories of nascent firms. In this paper, we investigate startup performance in the context of a significant but hitherto unexplored shift in the US startup investment landscape. In the aftermath of the 2009 Financial Crisis, increasingly younger firms became targets of relatively small first-round equity investments. As we show, early-stage first-round equity investments more than quadrupled between 2009 and 2013, a rise unparalleled by developments of other investment types or startup creation rates. This development triggered a major debate among practitioners voicing concerns about the potentially deteriorating performance of startups. Using investment and performance data on about 8,000 US-based startups, we provide a detailed portrayal of the implications of the *Seed Boom* for startup performance.

We find that a large share of initially *Seed*-backed startups are able to secure follow-on investments within the first years after the initial deal. Specifically, we do not find evidence that *Seed*-backed startups generally underperform comparable startups in terms of successful exits, follow-on investments, and IP generation. Based on this, we show that also the US *Seed Boom* during the early 2010s was not accompanied by a decline in startup performance, which is in line with the resource-based view, implying that entrepreneurial firms typically lack the needed resources to develop opportunities. VCs are specialized intermediaries that provide these resources. To show this, we separately investigate performance and liquidation rates among US-based startups. As a complementary approach, we show that there is also no relative decline in the performance of *Seed*-backed startups from the US relative to similar startups from the major VC markets outside the US. This finding is important as the (timing of the) *Seed Boom* is specific to the US. Finally, our analyses carve out potential mechanisms behind this resilience: They show that *Seed*-backed startups provide unique business opportunities serving as critical resources, which, however, need the complementary resources provided by VCs to unfold their full potential. In particular, based on a novel measure of startups' internet presence, we find that *Seed*-backed startups disproportionally pursued differentiation strategies, particularly after 2010. As a second mechanism, our analyses demonstrate that investors increasingly applied risk-mitigating strategies, such as portfolio diversification, as of 2010. These adjustments may have partially offset the high degree of uncertainty associated with particularly young ventures. Importantly, they allowed investors to provide critical resources needed to moderate financing and organizational resource constraints of *Seed*-backed startups.

These results have important managerial and economic implications. As such, they urge founders and managers to seek *Seed* investments even if their business has not yielded any tangible outcomes. In this context, our findings demonstrate the importance of pursuing differentiation strategies to survive in a competitive marketplace. From an investor's perspective, our findings show that young ventures are high-potential targets, but applying risk-mitigating strategies is crucial in accounting for the risk inherent to these startups. These results mitigate concerns raised by practitioners in entrepreneurial financing. Similarly, our findings are important from an academic perspective, as they shed light on a previously unexamined development in the financing landscape, whose effects are unclear a priori. We disclose that the significant shift in the US towards younger, riskier investment targets benefited well-performing startups. These insights highlight the potential of market forces and policy efforts to shape entrepreneurial financing and startup growth. Our results call for continued improvement of regulation to allow startups to get funded early on in order to adapt to ongoing transformations in the marketplace.

Despite all efforts, our analyses are not without limitations. Similar to most related studies, endogenous selection of the specific investment type may be an issue. Examining the factors that explain the endogenous sorting into initial obtaining *Seed* funding is beyond the scope of this study. A comprehensive survey of seed and VC funds and their startups is required to address the endogeneity issue. Likewise, quantifying the relative importance of specific factors that contributed to the rise in early-stage financing would be of interest. We leave this question for future research. Our analyses reveal insights on the significant shift in the US entrepreneurial financing landscape during the 2010s, assess potential causes, evaluate implications on startup performance, and provide the ground for future research on the increased use of small-scale, early-stage startup financing.

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Tables from the main part

Table 1: Summary statistics: First-round early-stage equity-backed startups

Panel A: Industry affiliations and geographical locations of first-round *Seed* targets

Business fields:		**Location (state):**	
Software	40.70	California	46.54
Internet Services	32.35	New York	17.86
Media & entertainment	29.02	Massachusetts	5.41
Mobile	20.53	Texas	2.84
Information technology	19.56	Washington	2.65
Data analytics	18.23	Illinois	2.73
Commerce & Shopping	16.78	Florida	1.62
Community & lifestyle	15.65	Others	20.35

(Share among total (in %))

Panel B: Startup performance indicators: succesful exits and follow-on funding

		First round 'seed'-backed startups		
	Full sample	**All**	**Until 2010**	**After 2010**
Exit, dummy	0.331	0.339	0.462	0.294
Acquisition, dummy	0.308	0.321	0.436	0.278
IPO, dummy	0.023	0.018	0.027	0.015
Nbr. funding rounds	3.111	3.272	3.642	3.134
Sum of funds collected (in mio. USD)	18.646	19.199	20.322	18.781
5 mio. collected, dummy	0.383	0.351	0.443	0.318
10 mio. collected, dummy	0.279	0.257	0.335	0.229
20 mio. collected, dummy	0.179	0.173	0.221	0.155
50 mio. collected, dummy	0.076	0.077	0.091	0.072
Obs.	7,964	4,183	1,127	3,056

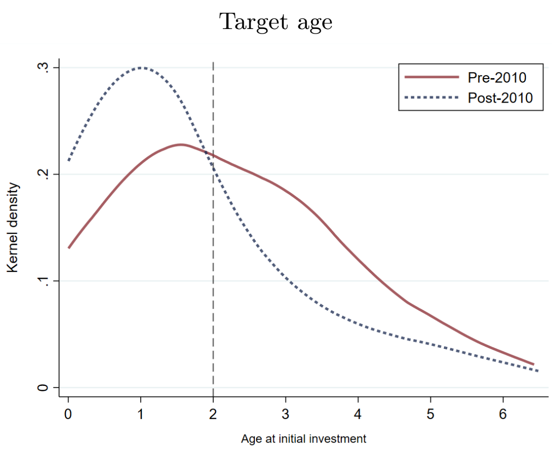
Notes: This Table displays summary statistics on firm-level data. Panel A displays the share of *Seed*-backed startups according to their main business fields and locations. Startups may have multiple business fields (i.e., the shares do not sum up to 100%) but only one location. Location indicates the state of the registered address of respective firms. Panel B displays statistics on 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 by 2014. Most 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. Only for the number of funding rounds and the sum of funds collected we use continuous variables. The table reports respective numbers for the full sample and for all startups with early first-round deals, further distinguishing whether first rounds are collected until 2010 or after.

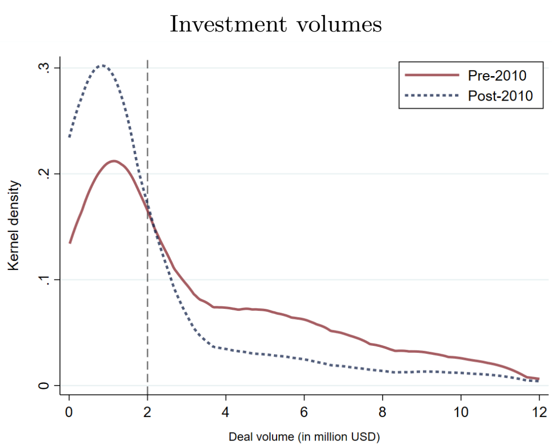
Table 2: Initial startup deals and the shift in target age and investment size (2005-2015)

Panel A: Descriptive statistics: Startups with early- and late VC deals as initial investment

	First-round deal type					
	Seed	Other	Seed-ratio	Startup creation	Seed/Creation ratio	Seed with subs. deal
2005	96	105	0.914	7,550	0.013	0.667
2006	123	160	0.769	8,118	0.015	0.675
2007	190	211	0.900	9,201	0.021	0.552
2008	195	231	0.844	9,980	0.020	0.472
2009	194	165	1.176	11,754	0.017	0.500
2010	329	222	1.482	13,091	0.025	0.505
2011	562	252	2.230	14,046	0.040	0.420
2012	769	274	2.807	15,770	0.049	0.397
2013	841	356	2.362	16,106	0.052	0.347
2014	884	473	1.869	16,425	0.054	0.355
2015	879	453	1.940	15,025	0.059	0.380

Panel B: Shift in the age and investment size distributions, pre- vs. post-2010





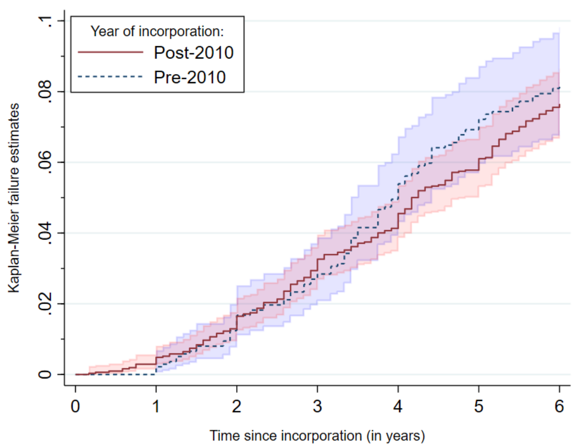
Notes: Panel A of this table displays the absolute numbers of first-round equity investments targets in the US from private investment funds. Corresponding to Figure 1 we distinguish targets younger (older) than two years and with a first round of less (more) than two million USD deal size, respectively. The third column is the ratio of *Seed* to "Other" first-round equity investments in respective years. The fourth column lists the total number of firms contained in the Crunchbase database that were founded in the US at any point during the respective calender years. The fifth column shows the ratio of initially *Seed*-backed startups as a fraction of the startups creation counts. The last column displays the share of initially *Seed*-backed startups that received subsequent equity funding. Panel B displays the kernel density distributions of target age and investment size on first-round early-stage VC investments. Target age is calculated as the 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 both graphs is 0.75. The dashed gray line resembles the classification thresholds as defined in Section 3.1.

Table 3: Performance implications of the *Seed Boom*

Panel A: Comparing pre and post 2010 success probability rates of *Seed*-backed startups

Dependent variable:	I(Performance indicators)					
	IPO	Acquisitions		Funds collected		
		All	>50 million	5 million	10 million	50 million
	(I)	(II)	(III)	(IV)	(V)	(VI)
Seed × Post^{2010}	-0.412	0.015	-0.377*	0.599***	0.372***	0.110
	(0.213)	(0.093)	(0.164)	(0.095)	(0.083)	(0.100)
Post^{2010}	-0.078	-0.269***	-0.070	-0.764***	-0.554***	-0.149*
	(0.146)	(0.065)	(0.129)	(0.053)	(0.052)	(0.069)
Seed	0.571***	0.416***	0.715***	0.491***	0.335***	0.335***
	(0.157)	(0.074)	(0.126)	(0.080)	(0.069)	(0.081)
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
N	4,560	4,560	4,560	4,560	4,560	4,560
Pseudo R^2	0.148	0.071	0.070	0.153	0.085	0.069

Panel B: Liquidation rates of 'Seed'-backed targets: before and after 2010s



Notes: Panel A shows results from probit regressions that use a set of performance indicators as dependent variables, estimating Equation 1. The estimation specification includes the dummy variable $Post^{2010}$ and its interaction with the *Seed*-indicator. $Post^{2010}$ equals one for all startups whose first investment round was announced after 2010, and zero otherwise. To avoid perfect multicollinearity, Panel B does include deal-year fixed effects. Again, 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 50 million USD valuation (Column III), or have collected at least 5, 10, or 50 million USD throughout (Columns IV – VI, respectively). Standard errors are clustered at the firm level. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively. The figure in 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.

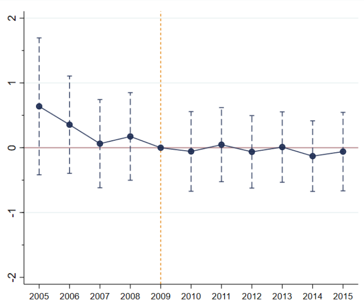
Table 4: Performance of US- and non-US startups subject to market- and policy-based changes

Panel A: Probit estimates on the likelihood of a successful startup performance

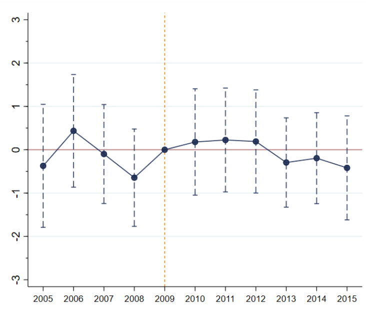
Dependent variable:	Performance indicators					
	Exits			Funds collected		
	All	IPO	Acquisitions	10 million	50 million	Total funds
	(I)	(II)	(III)	(IV)	(V)	(VI)
$Seed^{US} \times Post^{2010}$	-0.152	0.177	-0.179	-0.265*	0.026	-0.554
	(0.123)	(0.281)	(0.124)	(0.147)	(0.279)	(0.482)
Deal-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
N	3,389	3,213	3,389	3,389	3,296	3,389
Pseudo R^2 (R^{2}*)	0.031	0.051	0.031	0.061	0.041	0.091*

Panel B: Event-study type regression coefficient plots using different dependent variables

I(Exits)



I(Top exits)



Total funds collected

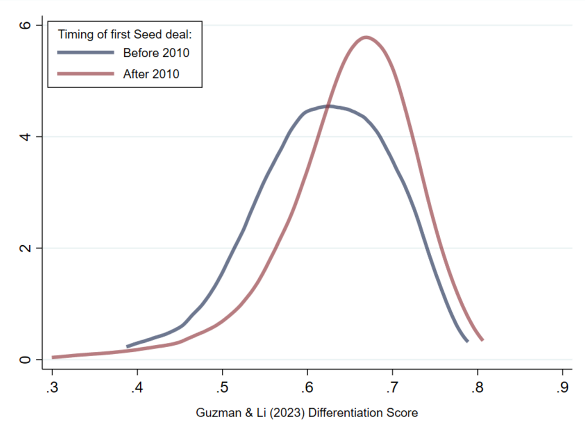
Notes: This Table displays variants of different estimates of Equation 2. In Panel A Columns I-V show results from probit regressions that use a set of performance indicators as dependent variables coded as dummy variables equal to one for startups that successfully exit (Column I), exit via IPO (Column II), exit via an acquisition (Column III), have raised at least 10 or 50 million USD (Columns IV and V, respectively). Performance outcomes are measured in the first eight years after incorporation and funding outcomes within the first five years, to avoid issues arising from right censoring of the data. In Column VI, we estimate the same equation using OLS. Here the dependent variable is a continuous measure for the funds collected within the first five years after incorporation. The data used is all firms that fulfill the *Seed*-backed venture category from both the main sample and respective firms from Israel, Canada, Great Britain, Germany, France, Sweden, and the Netherlands. Standard errors are clustered at the firm level. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively. Panel B displays the dynamic treatment effects (i.e., δ_k) estimated from the following equation: $P_i = \sum_k \delta_k (Seed_i^{US} \times Year_{ik}) + \delta_t + \delta_s + \delta_c + \epsilon_{ist}$ for all $k \in [2007, 2015]$, excluding 2009 as a reference year. The dependent variables are an indicator of startup exit equivalent to Column I in Panel A, an indicator only of those exits that are acquisitions of at least 50 million USD or an IPO, and the continuous measure on total funds collected equivalent Columns VI from Panel A. The whiskers span the 95 confidence intervals.

Table 5: Startup founding strategies and the *Seed Boom*

Panel A: Summary statistics: Startup differentiation scores

Competitor definition		Mean	Std. dev.	p10	p50	p90
Startups	Full sample	0.639	0.0770	0.54	0.65	0.72
	"Seed"-backed startups	0.642	0.0758	0.54	0.65	0.73
	Guzman & Li (2023)	0.654	0.0635	0.57	0.66	0.73
Public firms	Full sample	0.624	0.0834	0.51	0.64	0.72
	"Seed"-backed startups	0.635	0.0800	0.53	0.65	0.72
	Guzman & Li (2023)	0.635	0.0636	0.54	0.64	0.71

Kernel density plot (pre- and post-2010)



Panel B: Comparing differentiation scores with the original data

Dependent variable:	*Startup Differentiation*					
	(I)	(II)	(III)	(IV)	(V)	(VI)
$Post^{2010}$	0.028***	0.023***	0.010			
	(0.004)	(0.003)	(0.006)			
Seed		0.003	-0.008	-0.008	0.023***	-0.008
		(0.004)	(0.006)	(0.006)	(0.006)	(0.007)
Seed × $Post^{2010}$			0.018**	0.019**	0.015**	0.015*
			(0.007)	(0.007)	(0.007)	(0.008)
Differentiation definition:	Startups	Startups	Startups	Startups	Public firms	Startups
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Deal-year FE	No	No	No	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1,937	2,536	2,536	2,536	2,536	1,520
R^2	0.082	0.089	0.091	0.095	0.209	0.113

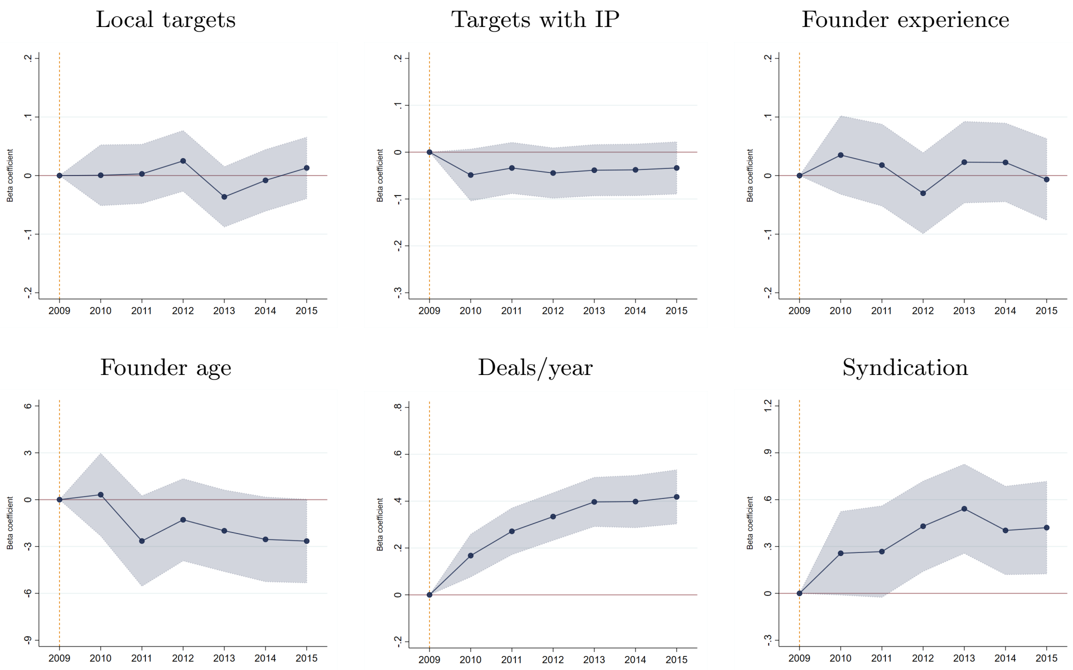
Notes: Panel A displays summary statistics on the differentiation scores obtained from Guzman and Li (2023). The displayed values are for all sample startups, initially *Seed*-backed startups, and the values from the original paper (Table 2 in Guzman and Li 2023). The graph below the table plots the density functions of initially *Seed*-backed targets over time, using the definition of five closest cohort startups to determine the distance to competitors. The graph plots respective distributions for all targets with an initial funding period not later than 2010 versus startups with an initial funding round after 2010, using a bandwidth of 0.3. Panel B displays a set of estimates obtained from different OLS regressions explaining startup differentiation scores, using the definition of five closest cohort startups to determine the distance to competitors. In Column I the sample is all *Seed*-backed startups. Columns II-V use the full sample, sequentially adding the *Seed*-dummy (Column II), the interaction term of $Seed \times Post^{2010}$ (Column III), and investment-year fixed-effects (Column IV). Column V is similar to the previous specification but uses the alternative definition of startup differentiation on public firms. Column VI is equivalent to Column IV but excludes initially *Seed*-backed targets without follow-on funding. Standard errors (in parentheses below coefficients) are clustered on the investor-level. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table 6: Changes of investment characteristics by US investors during the early 2010s

Panel A: Regression estimates explaining trends in investor motives relative to 2009

Strategies:	Risk-taking				Diversification	
Dep. variables:	Local targets	Targets with IP	Founder experience	Founder age	log(deals)	Nbr. coinvestors
	(I)	(II)	(III)	(IV)	(V)	(VI)
Trend × Seed$^{\text{inv.}}$	0.001	-0.003	-0.001	-0.342*	0.059***	0.045**
	(0.004)	(0.004)	(0.005)	(0.192)	(0.00910)	(0.023)
Additional controls:						
Investor-level	Yes	Yes	Yes	Yes	Yes	Yes
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes
State-year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	12,820	12,820	10,463	5,442	12,820	12,820
R^2	0.71	0.57	0.49	0.60	0.80	0.60

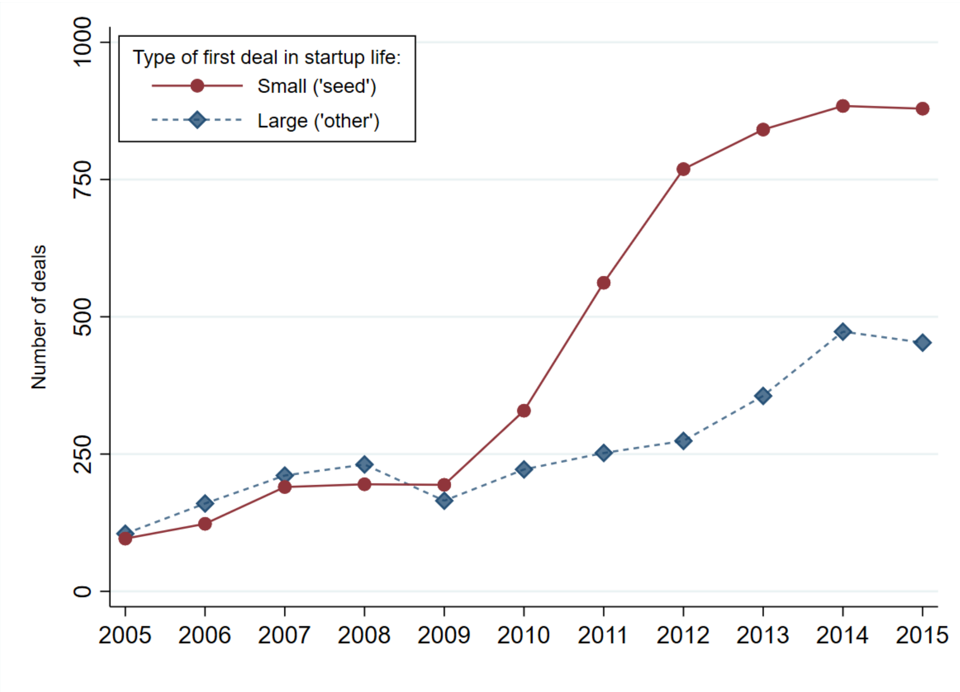
Panel B: Coefficient plot: Risk-taking and diversification strategy as investor motives



Notes: Panel A displays regression estimates as specified in Equation 3, explaining differential trends in investment characteristics of investors with and without *Seed* investments for the years 2009-2014. The six dependent variables in Columns I-VI are measures of risk-taking and diversification as introduced in Section 5.2. Standard errors (in parentheses below coefficients) are clustered on the investor-level. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively. In Panel B the graphs plot coefficients of event-study type regressions. Specifically, we estimate the following regression using the six variables of investment characteristics (Y_{it}) used in Panel A as dependent variables: $Y_{it} = \alpha_{ct} + \alpha_i + \alpha X_{it} + \sum_{S=2014}^{2010} \beta_{it}^{S} (Seed_i^{\text{inv.}} \times Year_t^{S}) + u_{it}$, where α_{ct} and α_i are state-year- and investor-fixed effects. X_{it} is a vector of investor-specific, time varying control variables, as defined in Equation 3. The graphs plot the β coefficients, which capture the interaction effect of year dummies for each year between 2010 and 2014 interacted with the $Seed^{\text{inv.}}$ dummy as defined in Equation 3. The year 2009 serves as a reference year. Regressions are estimated deploying an investor-year level database obtained from Crunchbase data. The shaded areas denote the 95 percent confidence intervals.

Figures from the main part

Figure 1: First time early-stage equity investments in the US by type

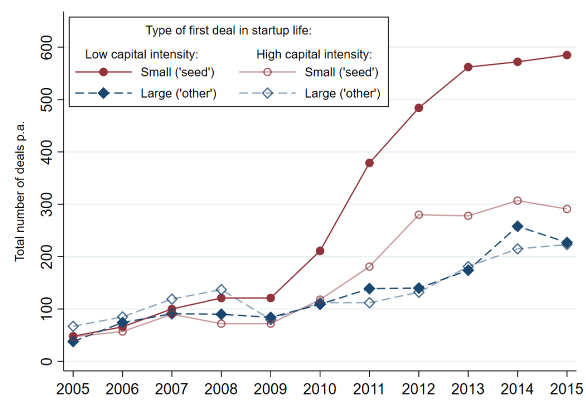


Notes: This figure illustrates the development of first-round equity investment deals for US-based investment targets in the years 2005-2015. The data is the universe of investment deals listed in the Crunchbase database for startups with US address, founded in 2002 or later, and with a first investment round between 2005 and 2015. The graph displays the absolute number of first-time financing events per year and per investment type. Specifically, it only considers the first ever entry in the Crunchbase data for any given startup. Here we refer to *Seed* or "Other" deals as any first time external equity investment that is conducted by an investment fund and has a maximum or minimum deal volume of 2 million US dollar provided for an investment target with a maximum or minimum age of 2 years at the time of the investment, respectively. Funds include all investors that are labeled as organizations (e.g., no individual investors) and exclude government or other public offices, incubators, accelerators, or angel groups.

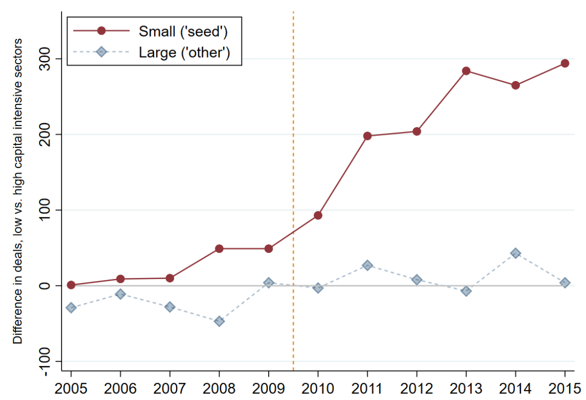
Figure 2: Factors driving the rise in early-stage startup financing

Panel A: Comparing targets from low and high capital intensive business fields

Annual number of deals

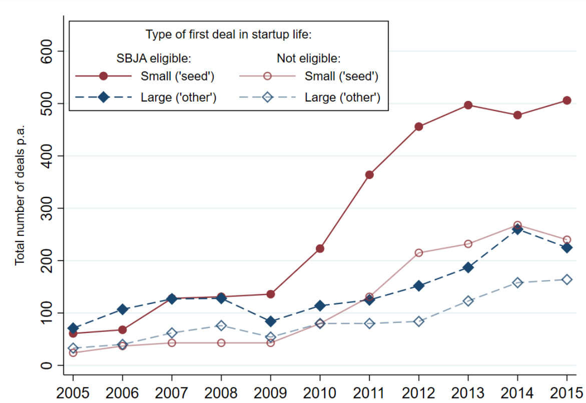


Difference in deals across sectors

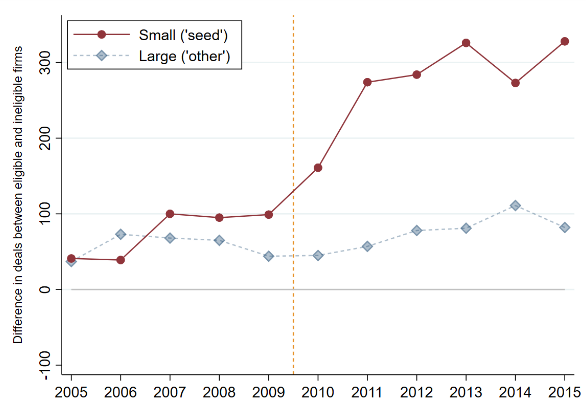


Panel B: Comparing targets eligible and ineligible to tax exemption under 2010 SBJA

Annual number of deals

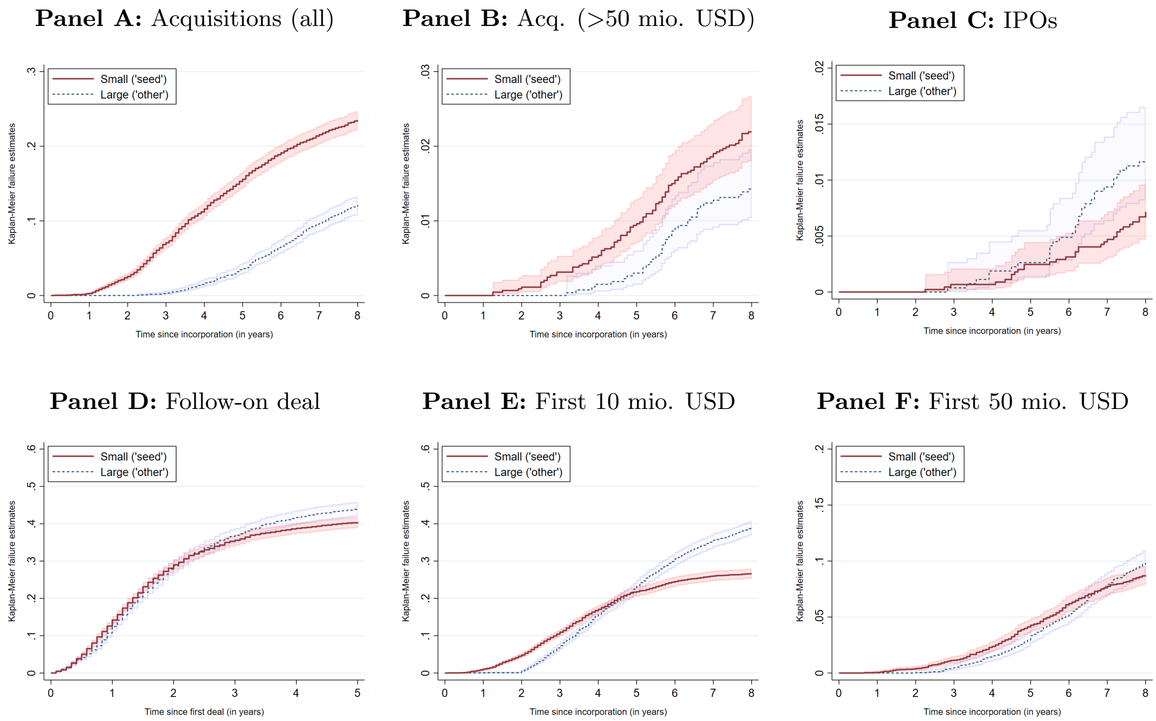


Difference in deals across sectors



Notes: Panel A displays the evolution of first-round *Seed*-backed US startups distinguishing among sectors with relatively low or high capital intensity as outlined in Section **??** and defined in Table IA5 (Appendix). For illustration, the graphs also display all other first-round equity-backed startups ("Other"). The left graph ("Annual number of deals") is similar to Figure 1 and plots the annual number of deals by respective cohorts. The right graph ("Difference in deals across sectors") displays 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, i.e., *Seed* and "Other". The dashed vertical line marks the onset of the accelerating shift towards younger and small targets as of 2010. All numbers are end-of-year total investment counts. Panel B repeats these graphs, however, this panel distinguishes firms that are active in sectors which are eligible to capital gains tax exemptions as stipulated in the SBJA as of September 2010 (as listed in Edwards and Todtenhaupt 2020).

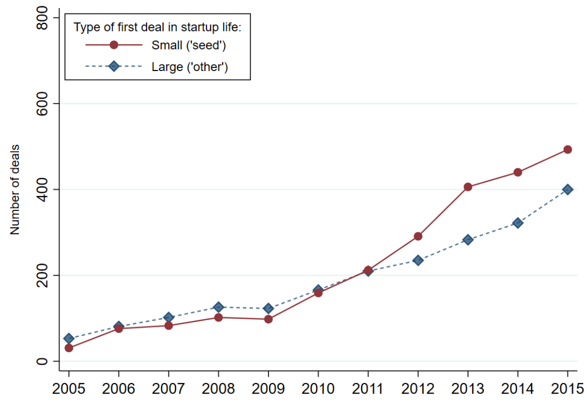
Figure 3: Startup performance over time: Time to a successful exits and follow-on funding of early-stage equity-backed startups



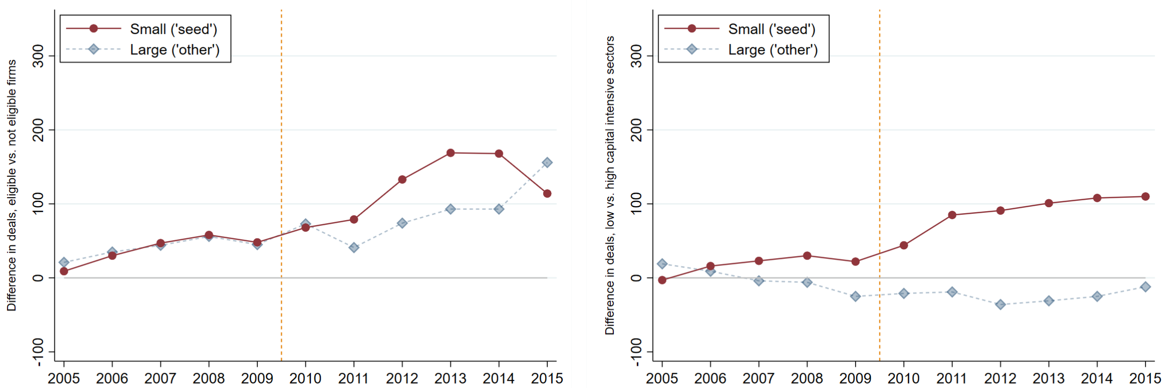
Notes: This graph investigates the time it takes a startup to achieve a certain performance target, i.e., a successful exit via an IPO or acquisition or the collection of follow-on investments distinguishing startups with initial *Seed* and "Other" first-round equity investments as defined in Section 3.1. The figure displays the probability of an acquisition (Panel A), acquisitions with a reported purchasing price of at least 50 million USD (Panel B), or a firm going public via an IPO (Panel C). The time is measures as of the date of incorporation. Moreover, Panel D reports the probability of receiving any subsequent funding of at least two million USD per round (measured since the initial funding round). Panels E and F report the time between incorporation and the date respective startups collect a total of 10 and 50 million USD in funding, respectively. To avoid right censoring issues, we measure all variables within the first eight years after incorporation and include startups founded by 2014. Only in Panel D, we consider the five years after initial funding to account for startup age at first funding. The shaded areas around the hazard rates mark the 95% confidence intervals.

Figure 4: The early-stage financing landscape outside the US

Panel A: First time early-stage equity investments in non-US startups



Panel B: Placebo test: Differences in early-stage financing – SBJA and low capital business fields



Notes: Panel A recasts Figure 1 using a sample of non-US based startups, headquartered in any of the seven economies with a most comparable VC-market relative to the US, i.e., Israel, Canada, Great Britain, Germany, France, Sweden, and the Netherlands. In Panel B we recast the right graphs ("Differences in deals across sectors") from the Figure 2 using the sample of non-US 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. The dashed vertical line marks the onset of the accelerating shift towards younger and small targets as of 2010. All numbers are end-of-year total investment counts.

FOR ONLINE PUBLICATION – Internet Appendix

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	224	4.43	30	1.03
Angel	274	5.41	24	0.83
Seed	3,954	78.11	578	19.92
Series A	448	8.85	1,297	44.69
Series unkown	162	3.20	973	33.53
Total	5,062	100.00	2,902	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 (variable *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"). Panel B displays the Crunchbase investor type categories (variable *investor_types*) assigned to each investor of all deals listed in Panel A.

Table IA2: List of variables

Main variables	Definitions
Main regressors	
Seed	Dummy variable taking a value of 1 for so-defined "Seed"-backed startups, i.e., that received first round equity investments by private funds with a maximum deal volume of two million USD targeted at firms within the first two years after incorporation; value 0 resembles startups that receive first round equity investments by private funds with a volume of more than two million USD and at a later age than two years.
$Seed^{US}$	Dummy variable taking a value of 1 for initially "Seed"-backed startups (as defined before) that are headquartered in the US and zero otherwise
$Post^{2010}$	Dummy variable taking a value of 1 for all years after 2010 and 0 for the years up until 2010
Startup and deal characteristics	
Target age	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 an investment fund
Investment volumes	Size of the initial equity investment that the focal startup received from an investment fund in millions USD
Investor-level outcomes	
Local targets	Dummy variable taking a value of 1 if investors and targets are headquartered in the same state
Targets with IP	Share of targets that hold IP rights (patents and trademarks) at the time of investment
Founder experience	Number of startups created prior to the founding of the founders of the focal startup
Founder age	Difference in days between their first university degree and the date of incorporation of the respective startup (divided by 365)
log(deals)	Total number of investment deals per year per investor (logged)
Nbr. coinvestors	Average number of co-investors per deal in a given year, indicating the syndication of deals

(continued on next page)

Table IA2: List of variables (*continued*)

Main variables	**Definitions**
Startup Performance Indicators	
Exit	Dummy variable taking a value of 1 if the startup exited either via an IPO or via acquisition within in the first eight years after incorporation
IPO	Dummy variable taking a value of 1 if the startup went public, i.e., exited via initial public offering within in the first eight years after incorporation
Acquisition (all >50 mill USD)	Dummy variable taking a value of 1 if the startup exited via an acquisition of any deal volume (including unknown volumes) and acquisitions with minimum 50 million USD valuation, respectively, within in the first eight years after incorporation
Intellectual property	Dummy variable taking a value of 1 if the startup filed for a patent of had a trademark registration within in the first eight years after incorporation
Funds collected (10 / 50 mill USD)	Dummy varible taking a value of 1 if the startup has raised at least 10 or 50 million USD in funding in total within in the first eight years after incorporation
Total funds collected	Accumulated deal volumes collected (in USD) by a startup within in the first eight years after incorporation
Startup Differentiation	Startup differentiation score, obtained from Guzman & Li (2023)

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: Business activities of *Seed*-backed targets before and after 2010

Pre 2010			Post 2010		
Rank	Business field	Share	Rank	Business field	Share
1.	Internet services	38.9	1.	Software	42.4
2.	Media and entertainment	34.3	2.	Internet services	30.9
3.	Software	33.3	3.	Media and entertainment	27.8
4.	Information technology	20.0	4.	Mobile	21.4
5.	Sales and marketing	19.6	5.	Data analytics	19.4
6.	Community and lifestyle	17.3	6.	Information technology	19.4
7.	Mobile	16.6	7.	Commerce & shopping	17.9
8.	Advertising	14.2	8.	Community and lifestyle	15.3
9.	Health care	13.2	9.	Health care	14.3
10.	Data analytics	12.9	10.	Sales and marketing	14.3

Notes: This table compares the composition of seed investment targets in our sample. It compares the composition of business activities in all years before 2010 and all subsequent years. Business activities are subcategories of the main industry field obtained from Crunchbase. Business activities are not mutually exclusive, but firms are often in more than one business field. The table compares the relative frequency of these activities (denoted as *Shares*) between the two periods focusing on the top 10 activities in the pre-2010 period. The only field present the pre-2010 (post-2010) period but not afterwards (before) is advertising (commerce and shopping).

Table IA5: 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 IA6: 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 tables display supplementary analyses to the basline estimations about startup performance. It displays the incidences of successful firm exits via acquisitions and IPOs and their funding history for the full Crunchbase sample on US-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 startups that received their first funding round of less than two million USD within the first two years after incorporation (*Seed*). 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 IA7: Probit regressions explaining performance outcomes of *Seed*-backed startups

Panel A: Matched sample - baseline analysis

Dependent variable:	I(Performance indicators)					
	IPO	Acquisitions		Funds collected		Intellectual
		All	>50 million	10 million	50 million	Property
	(I)	(II)	(III)	(IV)	(V)	(VI)
Seed	-0.698	0.422***	-0.288	-0.671***	-0.181	-0.585***
	(0.518)	(0.124)	(0.365)	(0.108)	(0.163)	(0.105)
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Deal-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1,700	2,021	1,895	2,021	2,021	2,021
Pseudo R^2	0.262	0.072	0.107	0.070	0.051	0.076

Panel B: Full sample, conditioning on *Seed*-backed startups with follow-on investments

Dependent variable:	I(Performance indicators)					
	IPO	Acquisitions		Funds collected		Intellectual
		All	>50 million	10 million	50 million	Property
	(I)	(II)	(III)	(IV)	(V)	(VI)
Seed	0.360***	0.402***	0.496***	0.573***	0.386***	0.040
	(0.106)	(0.048)	(0.087)	(0.042)	(0.051)	(0.042)
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Deal-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
N	4,560	4,560	4,560	4,560	4,560	4,560
Pseudo R^2	0.153	0.076	0.070	0.086	0.071	0.056

Panel C: Matched sample, conditioning on *Seed*-backed startups with follow-on investments

Dependent variable:	I(Performance indicators)					
	IPO	Acquisitions		Funds collected		Intellectual
		All	>50 million	10 million	50 million	Property
	(I)	(II)	(III)	(IV)	(V)	(VI)
Seed	0.063	0.223*	0.166	0.433***	0.446***	0.010
	(0.279)	(0.094)	(0.167)	(0.086)	(0.103)	(0.086)
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Deal-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
N	978	1,155	1,078	1,155	1,155	1,155
Pseudo R^2	0.153	0.076	0.070	0.086	0.071	0.056

Notes: This Table shows results from probit regressions that use a set of performance indicators as dependent variables, estimating Equation 1. 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 50 million USD valuation (Column III), have collected at least 10 or 50 million USD throughout (Columns IV and V, respectively), or have generated at least one patent or trademark throughout (Column VI). The estimates differ with regard to the sample used. Panel A uses the matched sample. Panel B uses the full sample but excludes initially *Seed*-backed startups that do not reach a subsequent VC-investment stage. Panel C uses the matched sample *and* excludes *Seed*-backed startups without follow-on investments. Standard errors are clustered at the firm level. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table IA8: Comparing pre and post 2010 success probability rates using split samples

Dependent variable:	I(Performance indicators)					
	IPO	Acquisitions		Intellectual	Funds collected	
		All	>50 million	Property	10 million	50 million
	(I)	(II)	(III)	(IV)	(V)	(VI)
	Investment years before 2010:					
Seed	0.617***	0.386***	0.731***	-0.037	0.299***	0.400***
	(0.164)	(0.088)	(0.150)	(0.082)	(0.083)	(0.098)
N	1,248	1,248	1,248	1,248	1,248	1,248
Pseudo R^2	0.152	0.077	0.134	0.052	0.052	0.091
	Investment years as of 2010:					
Seed	0.228	0.405***	0.398***	0.070	0.662***	0.382***
	(0.140)	(0.057)	(0.107)	(0.049)	(0.049)	(0.060)
N	3,312	3,312	3,312	3,312	3,312	3,312
Pseudo R^2	0.185	0.074	0.058	0.048	0.096	0.073
Controls in top and bottom panel:						
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Deal-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This Table shows results from probit regressions that use a set of performance indicators as dependent variables, estimating Equation 1, similar to Panel A of Table 3. Only here, the analysis are estimated separately for the subsamples of startups with the initial financing round before (top panel) and after 2010 (bottom). Standard errors are clustered at the firm level. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table IA9: Robustness test: The performance of US- and non-US-based startups after 2010

Panel A: Performance outcomes of startups in low capital intensive sectors

Dependent variable:	Performance indicators					
	Exits			Funds collected		
	All	IPO	Acquisitions	10 million	50 million	Total funds
	(I)	(II)	(III)	(IV)	(V)	(VI)
$Seed^{US} \times Post^{2010}$	-0.118	0.095	-0.139	-0.355**	0.072	-0.520
	(0.109)	(0.227)	(0.111)	(0.126)	(0.216)	(0.428)
Deal-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
N	4,546	4,314	4,546	4,546	4,486	4,546
Pseudo R^2 (R^{2}*)	0.029	0.051	0.029	0.042	0.031	0.075*

Panel B: Performance outcomes of startups in sectors subject to SBJA

Dependent variable:	Performance indicators					
	Exits			Funds collected		
	All	IPO	Acquisitions	10 million	50 million	Total funds
	(I)	(II)	(III)	(IV)	(V)	(VI)
$Seed^{US} \times Post^{2010}$	-0.196*	0.308	-0.218**	-0.274**	-0.219	-0.620
	(0.105)	(0.233)	(0.106)	(0.126)	(0.250)	(0.428)
Deal-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
N	4,684	4,438	4,684	4,684	4,547	4,684
Pseudo R^2 (R^{2}*)	0.029	0.033	0.029	0.063	0.042	0.100*

(continued on next page)

Table IA9: *continued*

Panel C: Triple-Differences estimations using the full sample

Dependent variable:	Performance indicators					
	Exits			Funds collected		
	All	IPO	Acqui.	10 mio.	50 mio.	Total funds
	(I)	(II)	(III)	(IV)	(V)	(VI)
$Sector^{\text{affected}} \times Seed^{\text{US}} \times Post^{2010}$	0.041	-0.149	0.039	0.090	-0.104	-0.551
	(0.180)	(0.371)	(0.183)	(0.195)	(0.300)	(0.722)
$Sector^{\text{affected}} \times Seed^{\text{US}}$	0.018	0.027	0.014	0.068	0.161	0.322
	(0.155)	(0.267)	(0.158)	(0.170)	(0.258)	(0.613)
$Seed^{\text{US}} \times Post^{2010}$	-0.191	0.359	-0.218	-0.486***	-0.083	0.023
	(0.134)	(0.237)	(0.137)	(0.139)	(0.204)	(0.540)
$Sector^{\text{affected}} \times Post^{2010}$	-0.078	0.106	-0.085	-0.102	-0.031	0.338
	(0.154)	(0.315)	(0.157)	(0.172)	(0.275)	(0.613)
$Sector^{\text{affected}}$	0.240*	-0.264	0.275*	-0.057	-0.136	0.373
	(0.132)	(0.215)	(0.135)	(0.150)	(0.237)	(0.521)
Deal-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
N	6,644	6,644	6,644	6,644	6,644	6,644
Pseudo R^2 (R^2*)	0.029	0.048	0.033	0.051	0.045	0.095*

Notes: This Table displays robustness tests on Section 4.2.2. Panels A and B are equivalent to Panel A of Table 4, only here the sample is either all US and non-US *Seed*-backed startups from sectors with low capital intensities (Panel A) or sectors subject to the SBJA (Panel B). In Panel C displays estimates on regressions using the full sample of *Seed*-backed firms, irrespective of the business field. The regression specification is similar to Equation 2 but adds an indicator $Sector^{\text{affected}}$, equal to one for all startups active in sectors that are subject to both market- and policy-related changes in the US and non-US startups active in the equivalent business sectors. Standard errors are clustered at the firm level. *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table IA10: Investor and founder 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 are displayed 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 variables refer to the first funding round: 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 US, 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.

Figure IA1: Stylized startup lifecycle – a traditional perspective

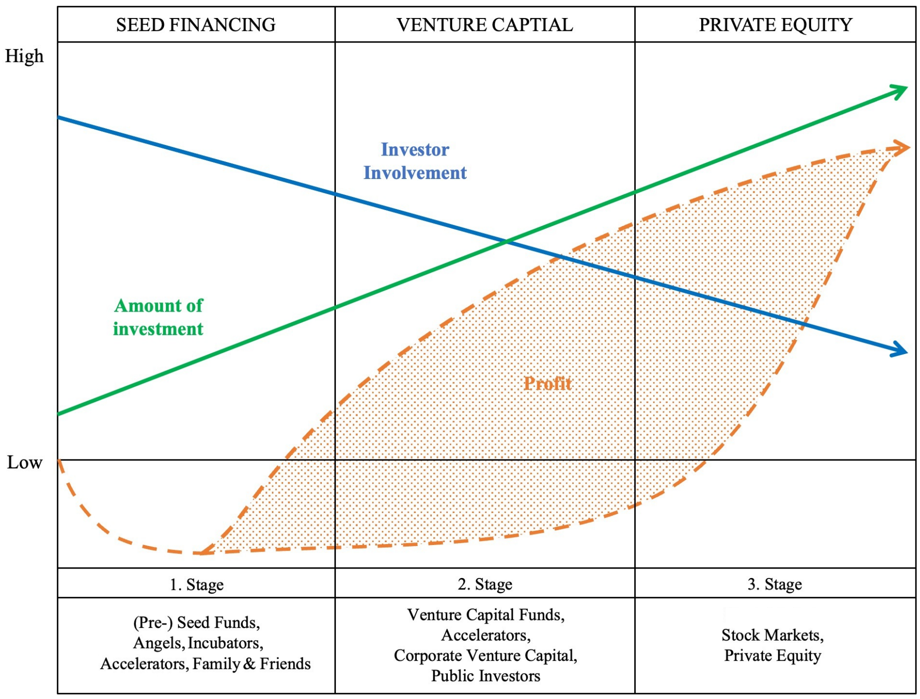
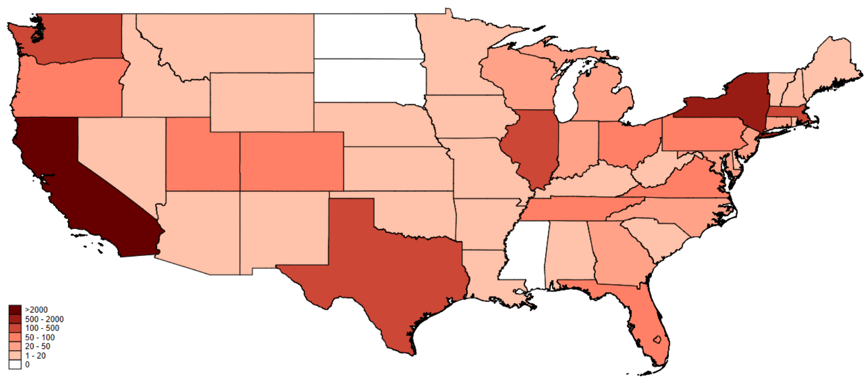


Figure IA2: Geographic locations of first-round equity investment targets, by type

'Seed'-backed targets:



'Other' first round targets:

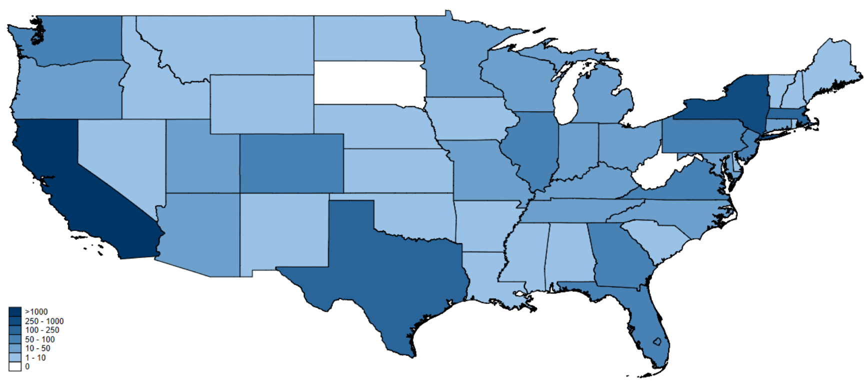
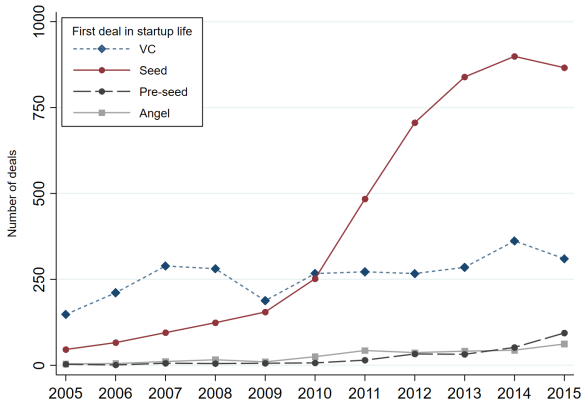
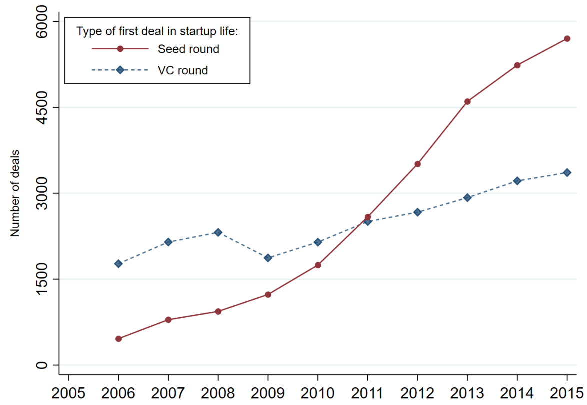


Figure IA3: Different perspectives on early-stage startup financing in the US (2005-2015)

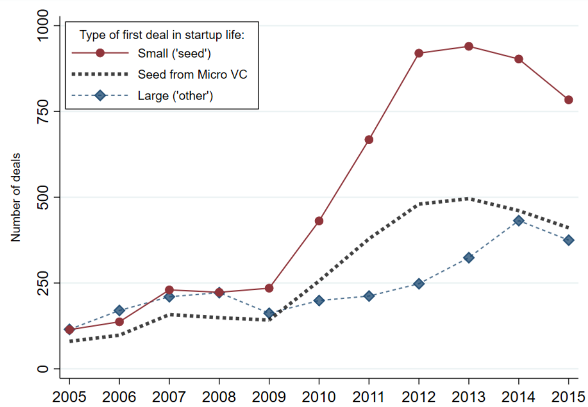
Panel A: Crunchbase investment classifications



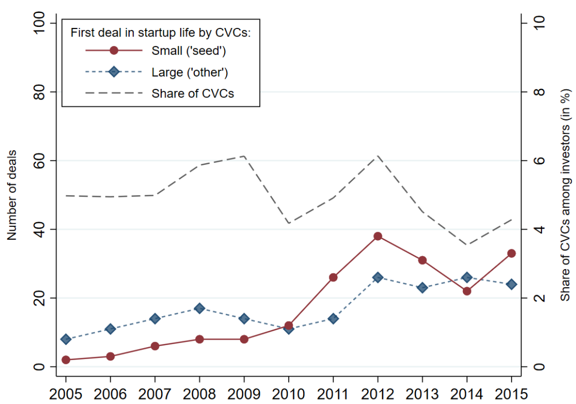
Panel B: Pitchbook data



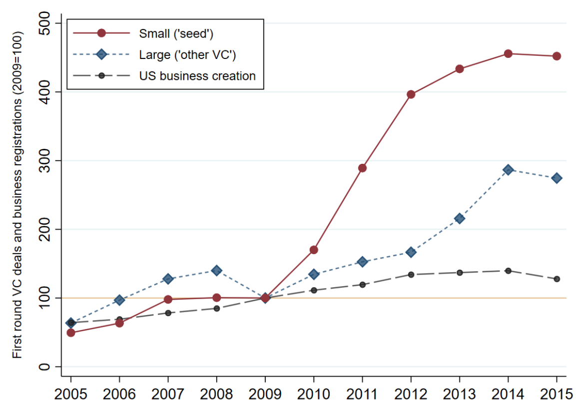
Panel C: Crunchbase investor type "venture capitalist" only



Panel D: Share of CVC investments



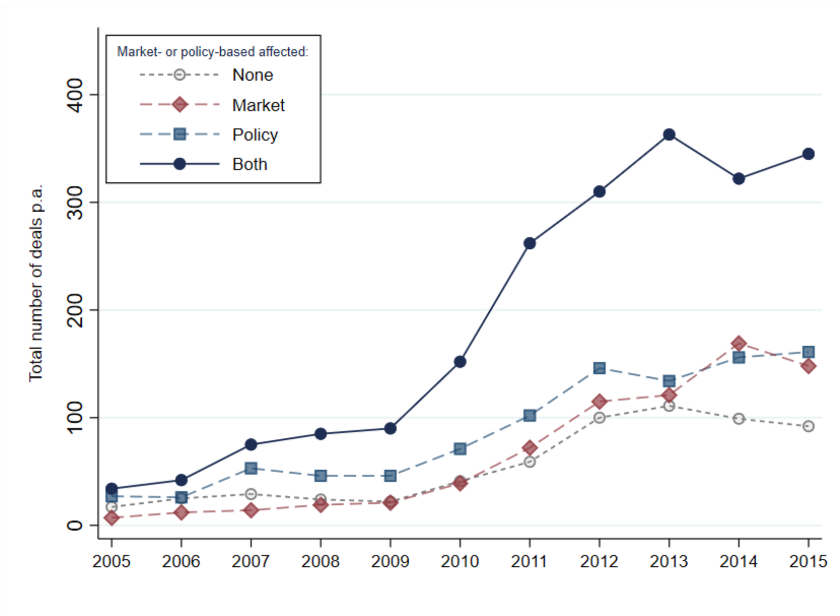
Panel E: Investments and business creation



Notes: This figure illustrates the development of early-stage equity financing activities for US-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 US 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 classifies first-round equity investments according to Crunchbase labels, distinguishing seed, pre-seed, angel, and VC rounds. Panel B 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 C excludes all startups without an investors that is labelled as "venture capitalist" or "micro VC" in the Crunchbase data. The dashed line resembles the number of Micro VC within this group. Panel D displays the shares of CVC investments within the first rounds observed in our data. Panel E plots the frequency of seed and later-staged deals like in Figure 1, only here the values are indexed with 2009 equal to 100. Additionally, the graph also plots the values of startup creation rates as displayed as in Table 2. Here, also startup creation rates are also expressed in 2009-indexed values.

Figure IA4: Disentangling the effect of market- and policy-based factors

Panel A: Annual number of deals



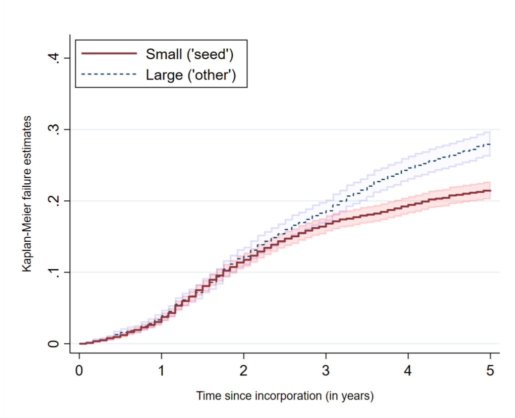
Panel B: Difference in deals across sectors

Notes: This graph displays the evolution of first-round *Seed*-backed US startups distinguishing firms that are either subject to both market- and policy-based factors, to none, or to only either one of them. The graphs are structured equivalent to those of Figure 2. Panel A plots the annual number of deals by respective cohorts. Only here, 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.

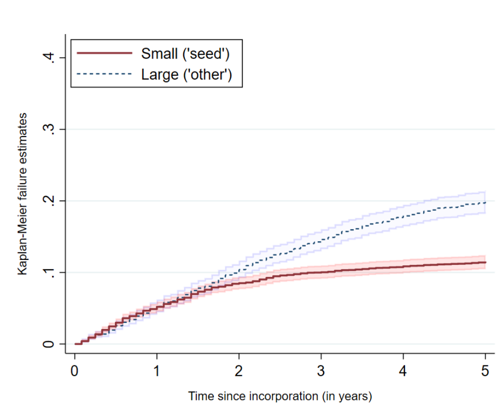
Figure IA4: Robustness tests on the timing of generating intellectual property rights

Panel A: Separating patent and trademark generation

Patent filings

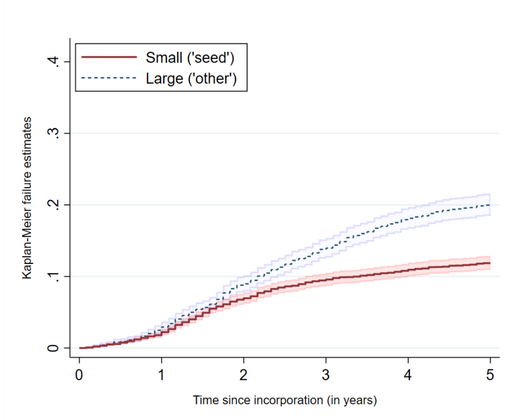


Trademark registration

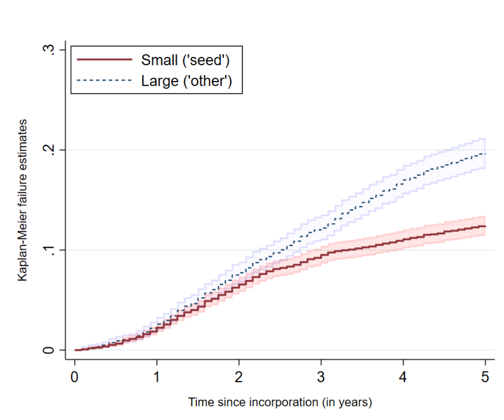


Panel B: Testing patent-quality adjustments

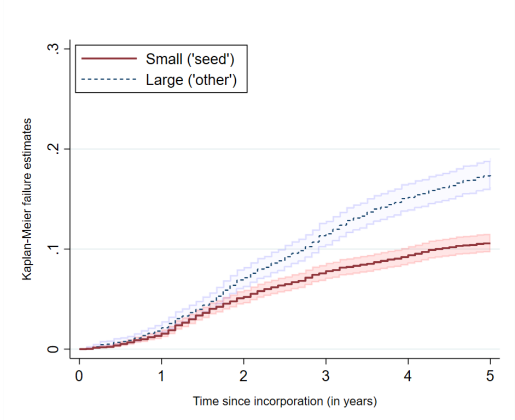
Forward citations



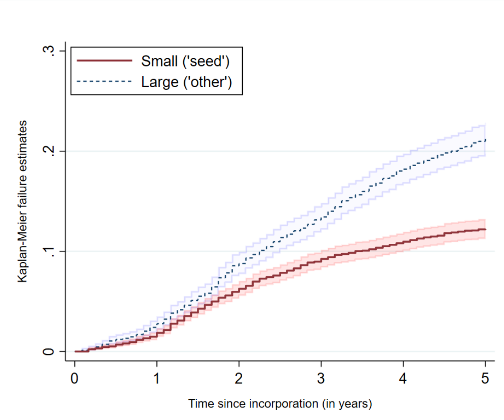
Originality index



Claims

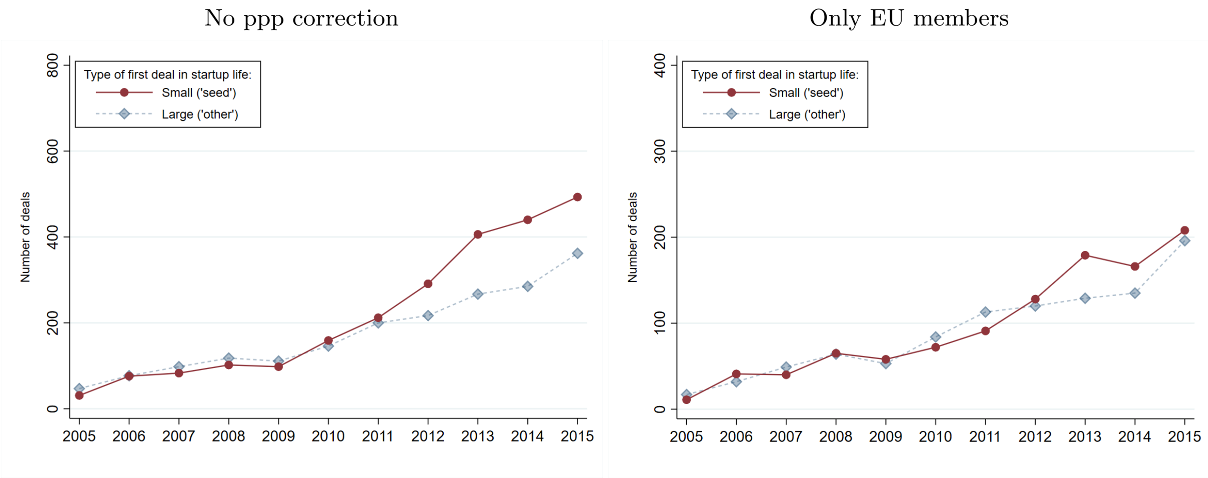


International applications



Notes: This graph is similar to Figure 3 and documents the timing of IP generation within the first five years after incorporation, distinguishing startups with initial *Seed* and "Other" first-round equity investments. Panel A displays the hazard rate for patents and trademarks separately. The graphs in Panel B are similar to the hazard rate on patents in Panel A but consider patents of high quality only. We use four measures of patent quality to determine high quality patents: patents with an above median i) forward citations (Harhoff *et al.* 2003), ii) originality index score (Hall *et al.* 2001), iii) number of claims (Marco *et al.* 2019), and iv) international patents, i.e., those that either have a triad or transnational patent application (Harhoff *et al.* 2003). To avoid truncation issues common to related literature, in Panel A we consider only citations within first five years after patent filing. The shaded areas around the hazard rates mark the 95% confidence intervals.

Figure IA6: Robustness test: Startup funding rates outside the US and alternative definitions



Notes: These figures recast Panel A of Figure 4. Only here we define the cutoff for early- and small VC deals without adjusting for the purchasing power parity (left panel). Alternatively, we exclude non-EU member states from the comparison group – Israel, Great Britain and Canada – because of the proximity in terms of entrepreneurial cultural to the US (right panel).