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Soutenue par

Caroline GENC

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Composition du jury :

Mme. Edith GINGLINGER Professeur de Finance, Université Paris Dauphine-PSL	<i>Présidente</i>
M. Michael EWENS Professor of Finance, Columbia Business School	<i>Rapporteur</i>
M. Ludovic PHALIPPOU Professor of Financial Economics, Said Business School	<i>Rapporteur</i>
M. David ROBINSON Professor of Finance, Duke Fuqua School of Business	<i>Examineur</i>
Mme. Catherine CASAMATTA Professeur de Finance, Toulouse School of Economics	<i>Examinatrice</i>
M. Gilles CHEMLA Directeur de Recherche CNRS, Université Paris Dauphine-PSL, Professeur de Finance, Imperial College London	<i>Directeur de thèse</i>

ESSAYS ON ENTREPRENEURIAL FINANCE

Caroline Genc

To my parents,

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General Introduction

Considering how essential the entrepreneurial activity of a country is for its economic growth, studying any aspect of entrepreneurship is highly valuable. The contribution of high-growth start-ups to the emergence of radical innovations makes research on entrepreneurship even more crucial for policy-makers. Indeed, innovation goes along with the creative destruction process and the productivity growth of economies (Schumpeter, 1942, Aghion and Howitt, 1992). Therefore, understanding the conditions under which potentially innovative firms can be developed and financed is very important. This Ph.D. dissertation aims to contribute to our understanding of these conditions. It consists of three chapters that mainly focus on re-entry into the entrepreneurial market and venture capital (VC) financing.

Due to the risk-return puzzle in entrepreneurship, there is a growing literature on entrepreneurial entry. Indeed, existing evidence suggests that entrepreneurs earn relatively low returns with respect to the risk they bear (Hamilton, 2000, Moskowitz and Vissing-Jørgensen, 2002, Hall and Woodward, 2010). Thus, alongside exploring founders' characteristics, motivations, and preferences to understand what makes an entrepreneur, existing studies investigate why some individuals enter and persist in entrepreneurship (see Astebro et al. (2014)). Non-pecuniary benefits, risk preferences, and behavioral explanations are the most explored reasons, among others (Kihlstrom and Laffont, 1979, Cooper et al., 1988, Puri and Robinson, 2007, Wasserman, 2008, Hvide and Panos, 2014, Catherine, 2022, Amornsiripanitch et al., 2022). Nevertheless, less is known about reentry in entrepreneurial markets.

The main challenge to studying serial entrepreneurship is obtaining well-suited data that enables tracking entrepreneurs over long periods. This is the primary reason behind the limited research on serial entrepreneurship. Most of the existing studies concern entrepreneurs who received venture capital financing. They highlight the persistence of success (Gompers et al., 2010) and stress that experienced founders obtain more favorable contracts than novice entrepreneurs (Hsu, 2007, Nahata, 2019). However, whether and how investors or founders value experience needs further clarification.

This is particularly important in an entrepreneurial context since the principal risk behind founding a new business is the risk of failure. Indeed, failure is the most frequently observed outcome in entrepreneurship (Sahlman, 2010, Kerr and Nanda, 2010, Hall and Woodward, 2010). Therefore, it concerns an important fraction of entrepreneurs overlooked in the entrepreneurial literature. There is still a lot to explore about the future career of these entrepreneurs, the motivations behind their decisions, and their willingness and likelihood to start new ventures. More specifically, since the perception of failure plays a critical role in such decisions, it requires more attention from researchers.

Understanding how entrepreneurial failure is regarded is crucial for multiple reasons. First, different perceptions of failure across countries (Burchell et al., 2006, Simmons et al., 2014) contribute to explaining cross-country variations in entrepreneurial market activity. Since some countries stigmatize failure, there are even debates around the optimal public memory of negative records, and second-chance policies appear on the agenda of regulators¹. Indeed, the way failure is perceived has significant consequences on the decisions of both entrepreneurs and investors. Individuals incorporate this perception into their decision to enter or re-enter the entrepreneurial market. Investors take this into consideration in their decision to finance entrepreneurs who have experienced failure. Therefore, it affects both the quality and the quantity of new businesses in a country.

In addition, the attitude toward failure is also shown to influence the degree of innovation. Indeed, Manso (2011) suggests that to motivate innovation, early failure should not be penalized, while long-term success should be rewarded. Evidence supporting this theory

¹See the second chance policy of the European Commission.

is provided through a laboratory experiment (Ederer and Manso, 2013). Tian and Wang (2014) show that this is also true for VC-backed companies: start-ups financed by more failure-tolerant investors are more innovative. Nanda and Rhodes-Kropf (2017) further suggest a contrasting view by focusing more specifically on radical innovation. They argue that failure-tolerant investors are more likely to select less radical innovations, while those who are not failure tolerant are more inclined to finance the most radical innovations. Hence, understanding whether and how the perception of failure affects a country's entrepreneurial activity has important implications.

Nevertheless, clarifying the optimal attitude toward entrepreneurial failure is a challenging task. We should first understand if entrepreneurs actually learn from their experience. If they do so, then facilitating reentry to both successful and unsuccessful entrepreneurs would be efficient. If not, then failed entrepreneurs should be treated equally with respect to new entrants. More specifically, if there is no evidence that entrepreneurs who experienced failure underperform first-timers, there is no reason to exhibit a preference for one or the other. If a preference exists, either failed entrepreneurs are stigmatized, or past experience is unduly overvalued. However, without letting these entrepreneurs reenter the entrepreneurial market in the first place, it is not possible to understand whether founder experience is valuable, whether they learn from it, or whether they simply miss entrepreneurial skills. Thus, what essentially matters is investors' priors about founders' experience and ability to learn from it. Therefore, examining how investors contribute to reentry into the entrepreneurial market is important. Among investors, venture capitalists are those mainly referred to in this dissertation.

Although VC-backed companies represent a very tiny portion of the newly created firms², venture capital is shown to be a central factor for economic growth and the funding of radical innovations (Kortum and Lerner, 2000, Samila and Sorenson, 2011). In addition, venture capital investors are different from other financial intermediaries. They do not restrict themselves to providing financial resources to early-stage start-ups. They also support them

²Puri and Zarutskie (2012) show that VC-backed firms correspond to 0.11% of their 25-year LBD sample while they account for 7.3% of employment in the US. In addition, Robb and Robinson (2014) point out that new firms rely substantially on debt financing, as opposed to some common priors.

through various post-investment services. Using their expertise, they may serve as mentors, provide access to their network and give valuable insights to avoid mistakes and increase the odds of success. Hence, both their selection process and their value-adding activities are worth studying. While this dissertation's first chapter mainly focuses on venture capitalists' selection process, its last chapter sheds light on their role vis-à-vis the re-entry of serial entrepreneurs and the value they potentially add to them. Indeed, the literature on the value-adding activities of venture capitalists does not provide evidence specific to serial entrepreneurs. Nevertheless, venture capital investors may have a noticeable impact on these entrepreneurs' experience and contribute to their learning. This may influence their perception of experience as well as of the founders' abilities to learn from failure.

Since perceptions are embedded into subjective beliefs, an overall analysis of subjective beliefs would be insightful in the entrepreneurial context. If investors' perceptions are important for their financing decisions, entrepreneurs' beliefs should not be neglected, especially because entrepreneurs are known to be particularly subject to some biases. Among the characteristics that set entrepreneurs apart from other individuals, optimism and overconfidence biases contribute to explaining entry and persistence in entrepreneurship. Camerer and Lovallo (1999) suggest that overconfident individuals are more prone to start businesses. De Meza and Southey (1996) argue that only optimists become entrepreneurs. While these two biases are related to each other, there is a subtle but notable difference between them³. Due to these biases, entrepreneurs overestimate not only their odds of success or the probability of having an operating venture but also their expected future sales and employment (Cooper et al., 1988, Cassar, 2010). Optimism also plays an interesting role in the entrepreneur's contractual choices. De Meza and Southey (1996) show that it leads to an equilibrium characterized by an excessive demand for debt over equity. Among different types of debts, optimism also explains the preference for short-term debts over long-term ones (Landier and Thesmar, 2009). These biases substantially affect career choices and economic decisions (Puri and Robinson, 2007, Astebro et al., 2014). Hence, whenever entrepreneurs' decisions to start a new venture are at play, the role of such biases should not

³I highlight this distinction more precisely below, in the summary of chapter 2.

be overlooked. The second chapter of this dissertation highlights the importance of such biases in accessing finance.

In a nutshell, the first chapter of this dissertation mainly concentrates on venture capital investors and the evolution of their investment model. Nevertheless, as it uncovers changes in venture capitalists' selection process, it still has implications for entrepreneurial entry. Chapters 2 and 3 particularly emphasize the perception and stigma of failure. While in the second chapter, I explore how behavioral biases affect the stigmatization of failure, in the last one, I question the perception of past experience and especially past failure experience in the US. I do so by focusing on serial entrepreneurs and their financing by venture capital investors. The remainder of this introduction summarizes each chapter separately.

The first chapter of this dissertation concerns venture capital investors and their selection process. It differs from the two other chapters as it does not focus on entrepreneurial reentry. However, it also contributes to understanding which type of entrepreneurs obtains VC financing. The primary goal of this chapter is to shed light on the importance of in-person interactions for the VC industry.

Indeed, since VCs invest in early-stage companies, they have little information about these latter. Therefore, both for their selection process and for their post-investment activities, VCs rely on the soft information they collect about their targets. Due to the difficulty of quantifying and transferring such information, they consider in-person interactions essential. This explains why VCs spend much time in networking events (Gompers et al., 2020) and locate in entrepreneurial clusters facilitating frequent face-to-face interactions (Sorenson and Stuart, 2001). However, whether these interactions are critical for the VC investment model or whether they are a result of historical norms has not been explored yet. Thus, this chapter aims to clarify the importance of in-person interactions for this industry by studying the consequences of restricting such interactions.

In this chapter, we exploit the sudden interruption of in-person communication due to the COVID-19 pandemic. This enables us to investigate changes in VCs' investment behavior when online meetings replace face-to-face interactions. We first explore whether

the geography of their investments is affected. Considering the difficulty and cost of distance communication, so far, distance has constituted an important barrier to soft information collection (Petersen and Rajan, 2002, Agarwal and Hauswald, 2010). With the restrictions on in-person interactions, investors were pushed to interact in the same way with all the firms: online. Consequently, this reduced the gap between proximate and distant companies regarding the quality of soft information and its cost of collection. Hence, since proximity is no longer advantageous in soft information collection, we expect VCs to broaden their horizons and invest in more distant companies. We then explore if VCs revise their selection criteria and proceed to syndication-related adjustments.

Regarding the geography of the investments, we find support for an increase in distance between VC firms and their portfolio companies. We show that this increase is about 43% in a cross-section of all first-round investments and about 27% within a VC firm. Our results further suggest that not only do VCs invest farther away, but they are also more likely to invest outside of their state. Moreover, when focusing on investments made in entrepreneurial hubs⁴, we notice some redistribution of the number of VC investments from these hubs toward non-hub areas. More specifically, hub VCs appear less inclined to invest in hub companies after the pandemic. This is not the case with VCs located outside the hubs. After the pandemic, these latter are as likely to invest in hubs as before.

Since the pandemic affected the overall economy, we try to exclude some alternative explanations in our analysis. First, we ensure that VCs do not invest in distant states due to the industry composition of these states. Indeed, if these states house industries that suffered less or benefited from the covid, the increase in the distance would be due to a specific focus on these industries. For that purpose, we control for the change in the industries' and states' growth rates, and we do not find support for this alternative explanation. Then, we rule out the possibility that this increase in distance is due to the fact that new businesses are created in states that are farther away. Controlling for the change in the growth rates of states' business applications before Covid enables us to exclude this second alternative hypothesis. Lastly, in all our distance-related regressions,

⁴Entrepreneurial hubs refer to San Francisco, San Jose, Boston, or New York.

we control for the total amount of capital raised by VC funds in the focal investor's state to ensure that the availability of high amounts of capital does not explain our results.

After this first set of findings about the geography of VC investments, we focus on changes in portfolio companies' characteristics. Under the assumption that in-person interactions are not critical to collect the information VCs used to have, we should not observe significant differences in companies' characteristics pre and post-covid. However, our findings show that, after covid, VCs invest in more mature companies and appoint fewer board members, even in proximate companies, on average. Interestingly, these are the features of typical pre-covid distant investments. Thus, online interactions do not seem to help overcome frictions traditionally associated with distance.

We then explore VCs' syndicate structure to analyze whether there are changes that may balance the modification of their information environment. Indeed, syndication is an important way to share risk, expertise, and opinions about investment opportunities. In that sense, we expect VCs to syndicate more due to higher informational frictions and uncertainty. Consistently, we find that VCs are up to 13% more likely to partner with other investors. We additionally observe that the average distance among syndicate members increases. Also, VCs are more likely to invest with old partners and at least one VC specialized in the company's industry. All this suggests that VCs leverage their network in a context where information collection is more challenging.

Lastly, we analyze the performance of the investments made before and after the pandemic. Although we need more time since its start to properly study performance, we provide some preliminary insights by relying on early performance indicators. Our primary proxy for performance is the probability of raising a second round of financing. We observe that within six months, there is no significant difference between companies that were first financed before Covid and those that received their first investment after. However, within 12 or 18 months, the difference becomes significant. Post-covid investments are more likely to benefit from a follow-up round than pre-covid investments. Similarly, we find that within 18 months, companies that received their first round after the pandemic are not less likely to exit fast. Nevertheless, these results should be corroborated with more data in the future

as exits usually require more time. Such an extension of our analysis will enable us to clarify the extent to which in-person interactions are essential for VCs and whether VCs efficiently adapted their investment model.

Thus, this first chapter contributes to understanding how VCs handled a shock that profoundly stressed their traditional investment model. It suggests that VCs balance their inability to collect information in person through changes in their selection and syndication process. Nevertheless, our findings reveal that they behave cautiously and make only small steps during their transition toward a new model. Overall, our results have important implications. They suggest that one main consequence of this new model will be the expansion of entrepreneurial activity and innovation spillovers outside traditional hubs. Such an implication raises questions about traditional clusters' role and importance. Our findings also support that online interactions might not enable VCs to collect the soft information they used to obtain through in-person interactions. This explains why they select companies that are more similar to distant companies in which they invested before the covid. Finally, our results also predict networks' increasing role as VCs rely more on syndicates to adapt to new environments.

The second chapter is the first one to focus on re-entry into entrepreneurship. It questions re-entry, especially after a failure and from a behavioral perspective. More precisely, it studies how behavioral biases affect the stigmatization of entrepreneurial failure. Since agency frictions play an important role in the financing of new ventures, the perception of these frictions is essential and highly related to investors' and entrepreneurs' beliefs. Thus, analyzing the perception of failure along with behavioral biases might have interesting insights for the financing of entrepreneurs who experienced failure in the past.

Considering that entrepreneurs are particularly subject to overconfidence and optimism biases (Cooper et al., 1988, Busenitz and Barney, 1997, Cassar, 2010), this chapter mainly focuses on these two biases. While overconfidence and optimism are frequently used interchangeably, I underline a non-negligible difference between the two notions. Moore and Healy (2008) provide three definitions of overconfidence based on overestimation, overplace-

ment, and overprecision. Indeed, overconfidence may first refer to the overestimation of one's actual ability or performance. It can also be considered as the overplacement of one's performance relative to others (known as the better-than-average effect). Lastly, overconfidence may be the overprecision of one's beliefs in an analysis (miscalibration). Regarding optimism, the definition is more general and supposes an overestimation of the likelihood of positive events and an underestimation of the likelihood of negative events (Weinstein, 1980). Thus, optimism does not necessarily refer to estimations related to one's involvement or ability. Therefore, while overconfidence is a form of optimism, the reverse is not true. In this chapter, by optimism, I refer to baseline optimism, that is, the case where there is no overconfidence at all. For overconfidence, I retain the definition corresponding to the overestimation of ability.

I theoretically study the emergence of stigma by embedding these well-documented entrepreneurial biases into a simple moral hazard framework. While most behavioral studies define either the principal or the agent as irrational, I consider both under subjective beliefs⁵. Indeed, in my set-up, subjective beliefs enable me to consider entrepreneurs' biases as well as investors' perceptions of failure. This latter is exogenous and introduces the notion of stigma to the model. I describe an entrepreneur (referred to here as 'she') as stigmatized if she has no access or costlier access to finance due to her past failure (Landier, 2005, Cahn et al., 2021) and not due to her actual type. This is a direct and observable stigma. However, she may also be indirectly stigmatized by the unobservable belief of the investor. If the investor (referred to here as 'he') has a negative perception of failure, he will undervalue the entrepreneur's ability due to her past failure. Since this does not always translate into an observable form of stigma, it is interesting to examine perceptions and decisions separately. In most studies, perceptions stay implicit, and the main focus is the observed stigma of failure. In addition, if the literature provides some evidence about the stigma of failure and its consequences, there is, to my knowledge, no research combining it with behavioral biases. Thus, this study is the first to cross behavioral biases and the stigma of failure. Moreover,

⁵This does not necessarily mean irrationality, when subjective beliefs fit with objective beliefs, individuals are regarded as rational or realistic. At the same time, if both the principal and the agent deviate from objective beliefs, they are both irrational.

building my analysis on a moral hazard problem enables me to distinguish overconfidence from optimism clearly. I show that such a distinction is quite relevant as the two biases play a different role in getting access to finance. Besides, I describe the consequences following the confusion of these two notions.

My main findings suggest that entrepreneurial overconfidence prevents stigma emergence while optimism alone should not. In the model, an investor has to choose between two projects: the one of a first-time entrepreneur and the one of a serial entrepreneur who has experienced failure. The main difference between the two choices is the history of the founder. Therefore, stigma emerges if the investor exhibits a preference toward the project of the first-time entrepreneur. I find that this is not the case under a moderate negative perception of failure (although not positive) when the entrepreneur is overconfident. The reason is that overconfident entrepreneurs require fewer shares than realistic or optimistic entrepreneurs to behave. Thus, overconfidence reduces the agency rent, and investors take advantage of this situation to extract more rent. This results in a preference for overconfident entrepreneurs, even if the latter have past failure experience. However, there is no preference for optimistic entrepreneurs who only overestimate the odds of success regardless of their effort. Therefore, optimistic entrepreneurs do not have more incentives to behave than realistic entrepreneurs.

In practice, recognizing optimistic entrepreneurs and those who are overconfident is challenging. It is then unsurprising to observe confusion between the two biases. Nevertheless, mistaking optimistic entrepreneurs for overconfident ones has many consequences. First, due to this confusion, optimistic entrepreneurs will also have easier access to financing despite eventual negative perceptions of failure. Second, since they will be offered a contract designed for overconfident entrepreneurs, they will still feel stigmatized due to the low share proposed. Third, having fewer incentives to behave due to this low stake will increase the probability of failure. Hence, confounding optimism and overconfidence leads investors to finance negative NPV projects.

This is not the only situation where investors finance negative NPV projects. I show that, although investors' subjective beliefs do not affect the optimal contract, they are essential

for decision-making. Optimistic investors may finance negative NPV projects, while pessimistic investors will miss positive NPV projects. More important, when investors are optimistic, entrepreneurial overconfidence fosters the excess financing of negative NPV projects. Therefore, when entrepreneurial overconfidence is predominant, it is socially more desirable to have realistic or even pessimistic investors. On the contrary, a remedy to investors' underfinancing of good projects due to high degrees of pessimism would be entrepreneurial overconfidence.

Besides, when investors do not hold negative beliefs about failure, stigma appears only in a subjective form. This essentially happens to entrepreneurs who are underconfident. Due to the high level of agency rent implied by underconfidence, this type of entrepreneur will not obtain financing. However, the underlying reason is not related to investors' perception of failure. Thus, there is no stigmatization of failure from an objective viewpoint. Nevertheless, from failed entrepreneurs' subjective viewpoint, such a decision may be perceived as stigmatization. When the investor overvalues knowledge acquisition through experience or learning from failure, this subjective stigma is less likely to appear. Indeed, as investors value past experience, failed entrepreneurs, although underconfident, have more chances to get financing than new entrants. In such a case, neither rational nor overconfident entrepreneurs are stigmatized.

Hence, this chapter suggests that there exist two ways to escape from the stigma of failure. First, investors should put enough weight on experience. Second, entrepreneurs should stay overconfident even though they have experienced failure. By taking a novel approach to analyzing the stigma of failure, this chapter contributes to both behavioral and entrepreneurial finance literature. It underlines that although being overconfident might be detrimental to entrepreneurs due to the low share they receive, it has positive effects on access to financing. Regarding empirical predictions, this chapter predicts that both overconfident and optimistic entrepreneurs are more likely to obtain funding for subsequent ventures after a failure compared to those who are realistic or those who became underconfident. If future research enables to distinguish optimism from overconfidence empirically, the observed likelihood of failure should be more substantial for optimistic entrepreneurs.

Lastly, due to the role of economic conditions on perceptions, they are also at play in accessing financing. Good times should welcome a less observable stigma of failure, and failures that occur during bad times should be less stigmatized.

The last chapter also concentrates on reentry into entrepreneurship. It questions the existence of an experimentation culture in the US entrepreneurial market and the contribution of venture capital investors to such a philosophy. Indeed, if “entrepreneurship is fundamentally about experimentation” (Kerr et al., 2014), entrepreneurs should not encounter many difficulties in trying again and starting new ventures. They should be encouraged to test new ideas regardless of their past outcome. Considering that failure is a more common event than success in entrepreneurship, it is crucial to understand how it is actually approached in this specific context. Usually, the US has a more welcoming reputation toward failure than many European countries, where it is negatively perceived and even stigmatized. Regarding entrepreneurial failure, while this latter constitutes a barrier to entering and reentering the entrepreneurial market in Europe (Cahn et al., 2021), mostly anecdotal evidence suggests that it is as celebrated as a success in the US. However, whether this positive perception of failure essentially refers to some success stories, and overlooks an important fraction of the failures, is still an open question. Also, since entrepreneurs need capital to experiment, investors’ attitude toward failure requires a particular investigation.

Among financial intermediaries, venture capitalists are of particular interest in this context. In addition to their active involvement in their portfolio companies that makes them different from other investors, they are also known for their specific capital infusion method: staged financing. Venture capitalists provide capital to start-ups round by round rather than upfront. They condition future financing upon the achievement of some milestones. Depending on the signal they receive, they terminate some investments to provide even more capital to more promising ventures. This enables them to initially invest in multiple ventures and give a chance to many founders. From that perspective, venture capital investors contribute to experimentation. However, do they especially facilitate experimentation for first-time entrepreneurs, or do they also help re-entry into the entrepreneurial market? More specifically, how do they consider past entrepreneurial experience?

To address these questions, I concentrate on serial entrepreneurship in the US and compare first-time entrepreneurs to second-time founders. I find support for both positive and negative views of failure. I first examine entrepreneurs' likelihood of starting a new business after experiencing failure. I notice that such an experience decreases the probability of reentering entrepreneurship compared to a successful experience. In addition, my results suggest that conditional on starting again, failed entrepreneurs are more likely to start in a different state or country. Although these are not causal evidence of a negative perception of failure, they trigger further motivation to explore what happens from a financing perspective.

Thus, I then analyze whether there are differences in the likelihood of raising venture capital funds between first-time and serial entrepreneurs. I find that past experience increases the probability of using VC financing if it is a successful experience. Regarding past failure, studying serial entrepreneurship overall reveals that failure is neither stigmatized nor positively valued. However, I show that these results should be carefully considered. Indeed, looking further among serial entrepreneurs indicates that these findings only hold for some types of serial founders. While some benefit from a positive perception of failure, others do not. I find that what determines the view of VCs on past experience is founders' past VC financing experience. Serial founders who obtained VC financing in their previous venture have more chances to raise capital in their focal firm, regardless of their past outcome. Conversely, for those who were never backed by VCs, past experience, including a successful one, does not increase the likelihood of obtaining VC financing compared to first-timers. On the contrary, past failure is shown to decrease this likelihood. Therefore, my findings suggest that, even in the US, past failures can be penalized. Whether this is stigmatization or whether venture capital investors have rational reasons to behave like this are the next questions I address.

For that purpose, I study and compare the future performances of the two groups of serial entrepreneurs. While a preference for previously VC-backed founders can be simply explained by an attempt to alleviate informational concerns through existing ties, it is still important to clarify if it is justified from a performance perspective. In addition, there are also performance-related explanations that might be at play and that require some attention.

First, just like they add value to companies (Hellmann and Puri, 2002, Hsu, 2006, Sørensen, 2007, Bottazzi et al., 2008, Chemmanur et al., 2011, Bernstein et al., 2016, Ewens and Marx, 2018), VCs might also add value to founders. If founders learn from them regardless of the outcome, VCs might be more confident in founders' ability to experiment efficiently and therefore exhibit a preference for those who have already entered their circle. Second, this group of serial founders might be attractive due to specific characteristics that increase their likelihood of success. Since previous VC investors have already selected founders, future investors may rely on prior VC experience when screening serial founders.

My overall results reveal that founders with past VC financing experience do not outperform those without. Therefore, I reject performance-driven explanations that assume a better performance from serial founders who have already experienced VC financing. VCs seem to favor previously backed entrepreneurs essentially due to their screening process. By reducing the differences between the profiles they select, they also decrease their chance of discovering new determinants of success and noticing that prior VC experience is not a reliable signal. Therefore, valuable opportunities might be overlooked by venture capital investors due to their focus on past VC financing experience or ties to VCs. In addition, while I confirm that success breeds success (Gompers et al., 2010), I do not observe any positive or negative effect of failure on success. Thus, I do not find performance-related reasons to prefer new entrants over entrepreneurs who experienced failure before and vice-versa. Hence, my results suggest that any preference for new entrants over failed entrepreneurs can be characterized as a stigma of failure.

This last chapter has important implications for both entrepreneurs and investors. Indeed, it reveals that, even in the US, starting a new venture after a failure is far from obvious. More specifically, although it supports the existence of a positive perception of failure, it also establishes that failure can be stigmatized. Nevertheless, both viewpoints are shown to be incorrect. While my results suggest that failure should not be stigmatized, they also indicate that it should not be overvalued. Failed entrepreneurs, on average, do not appear to learn from their past experiences. However, venture capital investors do both. First, they foster experimentation for those who have already obtained VC

financing in the past by overvaluing their experience. Second, they restrict experimentation for those who never received access to VC financing by stigmatizing failure. However, this last group of serial founders overperforms the former. Hence, there are valuable investment opportunities among serial entrepreneurs who are outside the VCs' field.

Introduction Générale

L'activité entrepreneuriale d'un pays est une composante essentielle de sa croissance économique. Etudier un quelconque aspect de l'entrepreneuriat relève donc d'une importance fondamentale. La recherche en entrepreneuriat est, d'autant plus cruciale, lorsque l'on considère la contribution des start-ups à fort potentiel de croissance, à l'émergence des innovations de rupture. En effet, la notion d'innovation va de pair avec le processus de destruction créatrice et la croissance de la productivité économique (Schumpeter, 1942, Aghion and Howitt, 1992). Par conséquent, l'étude des conditions sous lesquelles des entreprises potentiellement innovantes peuvent être développées et financées est primordiale. Cette thèse de doctorat vise à contribuer à notre compréhension de ces conditions. Elle est constituée de trois chapitres qui portent principalement sur le retour en entrepreneuriat ainsi que le financement par capital-risque.

Le rapport risque/rentabilité en entrepreneuriat est à l'origine d'une littérature de plus en plus abondante autour du choix de l'entrepreneuriat. En effet, les études existantes suggèrent que les entrepreneurs obtiennent des revenus relativement faibles par rapport au risque qu'ils supportent (Hamilton, 2000, Moskowitz and Vissing-Jørgensen, 2002, Hall and Woodward, 2010). Ainsi, en plus de leur volonté de définir un entrepreneur, à travers l'exploration des caractéristiques personnelles, motivations et préférences de ce dernier, les chercheurs s'intéressent également aux raisons pour lesquelles certains individus se lancent dans l'entrepreneuriat (Astebro et al., 2014). La motivation non pécuniaire, la préférence pour le risque ainsi que les explications d'ordre comportemental, sont les raisons, entre autres, les plus explorées (Kihlstrom and Laffont, 1979, Cooper et al., 1988, Puri and Robinson, 2007, Wasserman, 2008, Hvide and Panos, 2014, Catherine, 2022, Amornsiripan-

itch et al., 2022). Néanmoins, si l'initiation d'activités entrepreneuriales est relativement étudiée, nous en savons moins quant à la réinsertion des entrepreneurs existants sur le marché entrepreneurial.

Le principal défi de l'étude des entrepreneurs en série⁶ est l'obtention de données qui permettent de suivre les entrepreneurs sur de longues périodes. Cela explique pourquoi la recherche sur l'entrepreneuriat en série est limitée. La plupart des travaux existants sont restreints aux entrepreneurs qui ont obtenu un financement par capital-risque. Ils mettent en évidence la persistance du succès (Gompers et al., 2010) et les contrats plus favorables des entrepreneurs expérimentés relativement aux entrepreneurs novices (Hsu, 2007, Nahata, 2019). Cependant, la question de la perception de l'expérience, par les investisseurs ou par les entrepreneurs, nécessite davantage de clarifications.

Cette question est d'une importance particulière dans un contexte entrepreneurial puisque le principal risque lié à la création d'une nouvelle entreprise est l'échec. En effet, il s'agit du résultat le plus fréquemment observé en entrepreneuriat (Sahlman, 2010, Kerr and Nanda, 2010, Hall and Woodward, 2010). Cela concerne donc une fraction importante d'entrepreneurs qui ont néanmoins fait l'objet de très peu d'études dans la littérature. Ainsi, il reste encore beaucoup à explorer à propos de ces entrepreneurs qui ont échoué. Leur future carrière, les motivations derrière leurs décisions, leur volonté ainsi que leur possibilité de créer de nouvelles entreprises, sont tout autant de sujets qui nécessitent d'être examinés. Toutefois, étant donné que la perception de l'échec joue un rôle déterminant pour tout cela, elle nécessite une plus grande attention des chercheurs.

Comprendre la façon dont l'échec est appréhendé est essentiel pour plusieurs raisons. Tout d'abord, l'absence d'une vision unique de celui-ci au sein de tous les pays (Burchell et al., 2006, Simmons et al., 2014) contribue à expliquer pourquoi l'activité entrepreneuriale diffère d'un pays à l'autre. Puisque l'échec est stigmatisé dans certains pays, cela suscite même des débats au sujet de la mémoire optimale que l'on devrait avoir des événements négatifs. Des discussions autour des dispositifs de la deuxième chance figurent également à

⁶Les entrepreneurs en série sont ceux qui ont lancé plus d'une activité entrepreneuriale de manière séquentielle.

l'agenda des régulateurs ⁷. En effet, la manière dont l'échec est perçu a des conséquences importantes sur les décisions des entrepreneurs et des investisseurs. Les individus intègrent cette perception dans leur décision d'entrer ou de retourner sur le marché entrepreneurial. Les investisseurs en tiennent compte, quant à eux, dans leur décision de financement des entrepreneurs qui ont préalablement échoué. Par conséquent, la perception de l'échec affecte à la fois la qualité et la quantité d'entreprises nouvellement créées dans un pays.

De plus, il est également établi que l'attitude envers l'échec affecte le degré d'innovation. En effet, Manso (2011) soutient qu'afin de motiver l'innovation, l'échec précoce ne devrait pas être pénalisé, tandis que le succès de long terme devrait être récompensé. Des résultats à l'appui de cette théorie sont fournies par une étude expérimentale (Ederer and Manso, 2013). Tian and Wang (2014) montrent que cela est également vrai pour les entreprises financées par le capital-risque : les jeunes entreprises financées par des investisseurs plus tolérants à l'échec sont plus innovantes. Nanda and Rhodes-Kropf (2017) proposent une vision plus contrastée en se concentrant spécifiquement sur l'innovation radicale. Selon eux, les investisseurs tolérants à l'échec sont moins susceptibles de sélectionner des innovations radicales, tandis que ceux qui ne sont pas tolérants vis-à-vis de l'échec sont plus enclins à financer les innovations de rupture. Ainsi, comprendre si la perception de l'échec affecte l'activité entrepreneuriale d'un pays, et le cas échéant, la façon dont elle l'impacte, peut avoir de sensibles implications.

Il est toutefois difficile de déceler l'attitude optimale à adopter face à l'échec entrepreneurial. Cela suppose, dans un premier temps, de comprendre si les entrepreneurs tirent réellement des enseignements de leurs expériences. Si c'est bien le cas, faciliter la concrétisation des nouvelles initiatives de ces entrepreneurs pourrait être pertinent. Si ce n'est pas le cas, les entrepreneurs ayant échoué devraient être traités de la même manière que les nouveaux entrants. Plus précisément, si les entrepreneurs qui ont échoué ne sont pas moins performants que les entrepreneurs novices, il n'y a aucune raison d'avoir une préférence pour l'un ou l'autre des profils. La présence d'une quelconque préférence suppose, soit la stigmatisation des entrepreneurs qui ont échoué, soit la surestimation de l'expérience passée.

⁷Voir les dispositifs de la deuxième chance de la Commission européenne.

Afin de comprendre la valeur de l'expérience entrepreneuriale, de savoir si les entrepreneurs apprennent de leurs expériences, ou s'ils manquent simplement de potentiel, il faudrait en premier lieu leur permettre de réintégrer le marché de l'entrepreneuriat. Ainsi, ce sont les a priori des investisseurs, sur l'expérience des entrepreneurs et sur leur capacité à en tirer des leçons, qui importent essentiellement. Il est donc intéressant d'analyser comment les investisseurs contribuent à la réinsertion de ces créateurs d'entreprise sur le marché de l'entrepreneuriat. Parmi les investisseurs, les capital-risqueurs sont ceux qui seront principalement abordés dans cette thèse.

Bien que les entreprises financées par capital-risque ne représentent qu'une infime partie des entreprises nouvellement créées,⁸ le capital-risque s'avère être un facteur central de la croissance économique et du financement des innovations radicales (Kortum and Lerner, 2000, Samila and Sorenson, 2011). Outre cela, les investisseurs en capital-risque se démarquent des autres intermédiaires financiers. Ils ne se limitent pas à fournir des ressources financières aux jeunes entreprises en phase de démarrage. Ils les soutiennent également en leur fournissant divers services, à l'issue de l'investissement. Grâce à leur expertise, ils peuvent servir de mentors, permettre l'accès à leur réseau et fournir des informations précieuses afin d'éviter les erreurs et augmenter les chances de succès. Par conséquent, tant le processus de sélection des capital-risqueurs, que leurs activités post-investissement méritent d'être étudiés. Tandis que le premier chapitre de cette thèse se focalise sur le processus de sélection des capital-risqueurs, le dernier chapitre met en lumière leur rôle vis-à-vis des entrepreneurs en série. En effet, la littérature sur la valeur ajoutée du capital risque ne fournit pas d'éléments spécifiques aux entrepreneurs en série. Néanmoins, les capital-risqueurs peuvent avoir un impact notable sur l'expérience de ces entrepreneurs et contribuer à leur apprentissage. Cela pourrait alors affecter leur perception de l'expérience ainsi que de la capacité des entrepreneurs à tirer des leçons de l'échec.

⁸Puri and Zarutskie (2012) montrent que les entreprises financées par capital-risque correspondent à 0,11% de leur échantillon LBD sur 25 ans alors qu'elles représentent 7,3% de l'emploi aux États-Unis. En outre, Robb and Robinson (2014) soulignent que les nouvelles entreprises s'appuient substantiellement sur le financement par la dette, contrairement à la plupart des a priori.

Les perceptions étant intégrées dans les croyances subjectives, une analyse globale des croyances subjectives serait pertinente dans un contexte entrepreneurial. Si les perceptions des investisseurs sont importantes pour leurs décisions de financement, les croyances des entrepreneurs ne doivent pas être négligées, notamment en raison de leur particulière sensibilité à certains biais. Parmi les caractéristiques qui distinguent les entrepreneurs des autres individus, les biais d'optimisme et de surconfiance contribuent à expliquer leur préférence pour l'entrepreneuriat. Camerer and Lovallo (1999) suggèrent que les individus surconfiants sont plus enclins à créer des entreprises. De Meza and Southey (1996) soutiennent que seuls les optimistes deviennent des entrepreneurs. Bien que ces deux biais soient liés l'un à l'autre, il existe une différence subtile mais notable entre eux ⁹. En raison de ces biais, les entrepreneurs surestiment non seulement leurs chances de succès ou probabilité d'avoir une entreprise opérationnelle, mais aussi les niveaux de ventes et d'emplois futurs de leur entreprise (Cooper et al., 1988, Cassar, 2010). L'optimisme joue également un rôle intéressant dans les choix contractuels des entrepreneurs. De Meza and Southey (1996) montrent qu'il conduit à un équilibre caractérisé par une demande excessive de financement par dette, relativement au financement par action. Parmi les différents types de dettes, l'optimisme explique également la préférence pour les dettes de court terme par rapport aux dettes de long terme (Landier and Thesmar, 2009). De plus, ces biais affectent considérablement les choix de carrière et les décisions économiques (Puri and Robinson, 2007, Astebro et al., 2014). De fait, dès lors que des décisions de création d'entreprises sont en jeu, le rôle de ces biais ne doit pas être négligé. Le deuxième chapitre de cette thèse souligne l'importance de ces biais pour l'accès au financement.

En résumé, le premier chapitre de cette thèse porte principalement sur les capital-risqueurs et l'évolution de leur modèle d'investissement. Néanmoins, étant donné qu'il met en lumière les changements dans le processus de sélection des capital-risqueurs, il a des implications pour l'entrée dans l'entrepreneuriat. Les chapitres 2 et 3 mettent particulièrement l'accent sur la perception et la stigmatisation de l'échec. Tandis que dans le deuxième chapitre j'explore la façon dont les biais comportementaux affectent la stigmatisation de

⁹Les explications relatives à cette distinction sont fournies plus loin, dans le résumé du chapitre 2.

l'échec, dans le dernier chapitre, je questionne la perception de l'expérience et notamment de l'échec, aux États-Unis. Pour ce faire, je me concentre sur les entrepreneurs en série et leur financement par les capital-risqueurs. La suite de cette introduction résume chacun des trois chapitres de manière détaillée.

Le premier chapitre de cette thèse concerne les investisseurs en capital-risque et leur processus de sélection. Il diffère des deux autres chapitres car il ne se concentre pas sur la réinsertion en entrepreneuriat. Cependant, il contribue également à comprendre quel type d'entrepreneurs obtient un financement par capital-risque. Le principal objectif de ce chapitre est de mettre en lumière l'importance des interactions en présentiel pour l'industrie du capital-risque.

En effet, puisque les capital-risqueurs investissent dans des entreprises en phase de démarrage, ils disposent de peu d'informations sur ces dernières. Par conséquent, tant pour leur processus de sélection que pour leurs activités post-investissement, les sociétés de capital-risque s'appuient sur de l'information informelle ("soft information") qu'elles recueillent sur leurs cibles. En raison de la difficulté à quantifier et à transférer ces informations, les interactions en présentielles s'avèrent primordiales pour les capital-risqueurs. Ceci explique pourquoi les sociétés de capital-risque consacrent beaucoup de temps aux événements de réseautage (Gompers et al., 2020) et s'installent dans des clusters qui facilitent les fréquentes interactions en personne (Sorenson and Stuart, 2001). Cependant, la question de savoir si ces interactions sont essentielles pour le modèle d'investissement du capital-risque ou si elles sont le résultat de normes historiques, n'a pas encore été étudiée. Ce chapitre a donc pour intention de clarifier l'importance des interactions en personne pour cette industrie, en étudiant les conséquences d'une restriction de ces interactions.

Pour ce faire, cette étude exploite l'interruption soudaine de la communication en personne, en raison de la récente pandémie de COVID-19. Cela permet d'étudier les changements dans le comportement d'investissement des capital-risqueurs lorsque les réunions en personne font place aux réunions en ligne. La première partie de ce travail de recherche examine si la géographie des investissements est affectée. Compte tenu de la difficulté et du coût de la communication à distance, jusqu'à présent, la distance a constitué un obstacle

important à la collecte d'informations informelles (Petersen and Rajan, 2002, Agarwal and Hauswald, 2010). En raison des restrictions des interactions en présentiel, les investisseurs ont été poussés à interagir de la même manière avec toutes les entreprises, soit en ligne. Par conséquent, cela a réduit l'écart de qualité et de coût de collecte de "soft information" concernant les entreprises de proximité et les entreprises distantes. Ainsi, puisque la proximité n'est plus un avantage pour recueillir des informations de type informelles, l'on s'attend à ce que les sociétés de capital-risque élargissent leurs horizons et investissent dans des entreprises plus éloignées. Il est également plausible que ces investisseurs révisent leurs critères de sélection et procèdent à des ajustements liés à leur syndication, afin de compenser leur accès réduit au type d'information qu'ils avaient l'habitude d'obtenir.

Pour ce qui est de la géographie des investissements, un accroissement de la distance entre les sociétés de capital-risque et leurs entreprises cibles est observé. Cette augmentation est d'environ 43% dans une analyse de tous les premiers investissements, en coupe transversale, et d'environ 27% au sein même d'une société de capital-risque. De plus, les résultats de l'étude insinuent que non seulement les sociétés de capital-risque investissent plus loin, mais qu'elles sont également plus susceptibles d'investir en dehors de leur Etats. Aussi, lorsque l'on se concentre sur les investissements réalisés dans les "hubs entrepreneuriaux" (San Francisco, San Jose, Boston ou New York), l'on constate une certaine redistribution du nombre d'investissements de ces hubs vers les zones hors hubs. Plus précisément, les capital-risqueurs qui se situent eux-mêmes dans les hubs, semblent moins enclins à investir dans les entreprises des hubs après la pandémie. Ce n'est, toutefois, pas le cas des sociétés de capital-risque situées en dehors des hubs. Après la pandémie, ces dernières sont tout aussi susceptibles d'investir dans les hubs qu'auparavant.

La pandémie ayant affecté l'ensemble de l'économie, cette recherche exclut certaines explications alternatives. Tout d'abord, la possibilité que les sociétés de capital-risque investissent dans des États éloignés, en raison de la composition industrielle de ces États, est éliminée. En effet, si ces États abritent des industries qui ont moins souffert ou même bénéficié de la pandémie, l'augmentation de la distance serait due à une concentration spécifique de ces industries dans ces États. Ainsi, des tests additionnels sont réalisés avec des

régressions qui incluent des variables de contrôle pour l'évolution des taux de croissance des industries et des États. Le résultat principal ne semble pas être justifié par cette explication alternative. Est également exclu le fait que cette augmentation de la distance puisse être expliquée par la localisation plus éloignée des entreprises nouvellement créées. Le contrôle de l'évolution des demandes de création d'entreprises, pour chaque Etat, écarte cette deuxième hypothèse alternative. Enfin, toutes les régressions liées à la distance contiennent une variable de contrôle pour le montant total des capitaux levés par les fonds de capital-risque, dans l'État de l'investisseur focal. Cela assure que l'abondance de capital n'explique pas les résultats observés.

Ce chapitre expose ensuite les changements des caractéristiques des entreprises ciblées. En partant du postulat que les interactions en personne ne sont plus indispensables pour recueillir les informations que les investisseurs pouvaient détenir auparavant, il ne devrait pas y avoir de différences significatives dans les caractéristiques des entreprises financées avant et après la pandémie. Cependant, après l'émergence de la COVID-19, les capital risqueurs semblent investir dans des entreprises plus matures et nomment, en moyenne, moins de membres du conseil d'administration, y compris dans les entreprises proches. Il est intéressant de noter que ce sont là les caractéristiques des investissements à distance typiques de la période pré-covid. Ainsi, les interactions en ligne ne semblent pas aider à surmonter les frictions traditionnellement associées à la distance.

La structure des syndicats de capital-risque est également analysée afin de déterminer s'il existe des changements pouvant compenser l'évolution de leur environnement informationnel. En effet, la syndication est un moyen important de partager le risque, l'expertise et les opinions sur les opportunités d'investissement. En ce sens, les capital-risqueurs devraient se syndiquer davantage en raison de frictions informationnelles et du degré d'incertitude plus élevé. C'est ce qu'il ressort des résultats de cette étude : les sociétés de capital-risque sont jusqu'à 13% plus à même de s'associer à d'autres investisseurs. Un second constat est que la distance moyenne entre les membres des syndicats augmente également. De plus, les sociétés de capital-risque sont davantage susceptibles d'investir avec d'anciens partenaires ainsi qu'au moins un investisseur spécialisé dans le secteur de l'entreprise cible. Tout ceci

suggère que les capital-risqueurs tirent parti de leur réseau dans un contexte où la collecte d'informations est plus difficile.

Enfin, ce chapitre comporte une analyse de la performance des investissements réalisés avant et après la pandémie. Bien qu'une plus longue période de temps soit nécessaire pour une étude de performance, cette analyse préliminaire permet une première approche des résultats en s'appuyant sur des indicateurs de performance précoces. Le principal indicateur de performance est la probabilité d'obtenir un deuxième tour de financement. Lorsque l'on se concentre sur les six premiers mois qui suivent le début de la pandémie, l'étude révèle une absence de différence significative entre les entreprises qui ont reçu leur premier financement avant la pandémie et celles qui l'ont reçu après. Cependant, dans les 12 ou 18 mois qui suivent la pandémie, une différence significative apparaît. Les investissements post-pandémiques ont plus de chance de bénéficier d'un second tour de financement que les investissements pré-pandémiques. De même, dans les 18 mois qui suivent le premier financement, les entreprises qui ont reçu ce dernier après la pandémie ne sont pas moins susceptibles de s'introduire en bourse ou de se faire acquérir. Néanmoins, ces résultats devraient être corroborés par davantage de données à l'avenir car les introductions en bourse et les acquisitions nécessitent généralement plus de temps. Une telle extension de ce travail permettra de clarifier dans quelles mesures les interactions en personne sont essentielles pour les capital-risqueurs et si ces derniers ont efficacement adapté leur modèle d'investissement.

Ainsi, ce premier chapitre contribue à comprendre comment les sociétés de capital-risque ont appréhendé un choc qui a profondément mis à mal leur modèle d'investissement traditionnel. Il suggère que les sociétés de capital-risque compensent leur incapacité à recueillir des informations en personne par des changements dans leur processus de sélection et de syndication. Néanmoins, les résultats révèlent que les capital-risqueurs se comportent avec prudence et avancent lentement lors de leur transition vers un nouveau modèle. Dans l'ensemble, ces résultats ont d'importantes implications. Parmi les principales conséquences potentielles de ce nouveau modèle, nous pouvons compter l'expansion de l'activité entrepreneuriale, ainsi qu'un possible effet de contagion, en termes d'innovation, en dehors des hubs traditionnels. Une telle conséquence soulève naturellement des questions sur le

rôle et l'importance des clusters traditionnels. Les résultats obtenus confirment également que les interactions en ligne ne permettent pas aux investisseurs de capital-risque de recueillir les informations “informelles”, qu'ils avaient l'habitude d'obtenir grâce aux échanges en présentiel. Cela explique pourquoi ils sélectionnent maintenant des entreprises qui ressemblent davantage aux entreprises distantes typiques dans lesquelles ils investissaient avant la pandémie. Enfin, les capital-risqueurs s'appuyant davantage sur les syndicats d'investisseurs afin de s'adapter à un nouvel environnement, un rôle croissant des réseaux de capital-risque est attendu.

Le deuxième chapitre est le premier à traiter de la réinsertion sur le marché entrepreneurial. Il s'intéresse à la question d'une nouvelle tentative entrepreneuriale, notamment après un échec et sous une perspective comportementale. Plus précisément, il décrit la façon dont les biais comportementaux affectent la stigmatisation de l'échec entrepreneurial. Puisque les frictions informationnelles jouent un rôle important dans le financement des nouvelles entreprises, la perception de ces frictions est essentielle et fortement liée aux croyances des investisseurs et des entrepreneurs. Ainsi, l'analyse de la perception de l'échec et des biais comportementaux pourrait apporter des connaissances intéressantes quant aux financements des entrepreneurs qui ont connu un échec.

Les entrepreneurs étant particulièrement sujets aux biais de surconfiance et d'optimisme (Cooper et al., 1988, Busenitz and Barney, 1997, Cassar, 2010), ce chapitre se concentre principalement sur ces deux biais. Bien que la surconfiance et l'optimisme soient souvent utilisés de manière interchangeable, il existe une différence non négligeable entre ces deux notions. Moore and Healy (2008) fournissent trois définitions de la surconfiance basées sur la surestimation, le surplacement et la surprécision. En effet, la surconfiance peut désigner la surestimation, par un individu, de ses capacités ou de ses performances réelles. Il peut également être considéré comme un meilleur positionnement, à tort, de sa performance par rapport aux autres (connu sous le nom du “better than average effect”). Enfin, la surconfiance peut correspondre à une confiance excessive en ses connaissances (“miscalibration”). En ce qui concerne l'optimisme, sa définition est plus générale et suppose une surestimation de l'occurrence d'événements positifs et une sous-estimation de la survenue d'événements

négatifs (Weinstein, 1980). Ainsi, l'optimisme ne fait pas nécessairement référence à des estimations liées à la capacité ou l'implication d'une personne. Par conséquent, si la surconfiance est une forme d'optimisme, ce dernier n'est pas nécessairement une forme de surconfiance. Dans ce chapitre, par optimisme, je sous-entends l'optimisme de référence, c'est-à-dire le cas où il n'y a pas du tout de surconfiance. Pour la surconfiance, je retiens la définition correspondant à la surestimation des capacités.

J'analyse, sous un angle théorique, l'émergence de la stigmatisation de l'échec, en intégrant ces biais comportementaux dans un cadre d'aléa moral classique. Tandis que la plupart des études comportementales définissent le principal ou l'agent comme étant irrationnel, dans ce chapitre, je les analyse tous deux sous l'angle des croyances subjectives¹⁰. Cela me permet de grouper sous ces croyances subjectives, à la fois les biais des entrepreneurs et la perception de l'échec par les investisseurs. Cette dernière est exogène et permet d'introduire la notion de stigmatisation dans le modèle.

Un entrepreneur est considéré comme étant stigmatisé, s'il n'a pas accès au financement ou si le financement lui coûte plus cher en raison de son échec antérieur (Landier, 2005, Cahn et al., 2021) et non en raison de son type réel. Cela correspond à une stigmatisation directe et observable. Cependant, il peut également être indirectement stigmatisé par les idées préconçues de l'investisseur qui ne sont pas nécessairement observables. Si l'investisseur a une perception négative de l'échec, il sous-évaluera la capacité de l'entrepreneur en raison de ses échecs passés. Puisque cela ne se traduit pas toujours par une forme observable de stigmatisation, il est intéressant d'étudier distinctement les perceptions et les décisions. Dans la plupart des études, les perceptions restent implicites et l'accent est mis sur la stigmatisation observable de l'échec. S'il existe quelques travaux sur la stigmatisation de l'échec et ses conséquences, il n'existe, à ma connaissance, aucune recherche la combinant avec les biais comportementaux. Ainsi, cette étude est la première à croiser les biais comportementaux et la stigmatisation de l'échec. De plus, baser mon analyse sur un problème d'aléa moral me permet de distinguer clairement la surconfiance de l'optimisme. Une telle distinction est

¹⁰Cela ne suppose pas nécessairement l'irrationalité. Lorsque les croyances subjectives correspondent aux croyances objectives, les individus sont considérés comme rationnels ou réalistes. Si le principal et l'agent s'écartent des croyances objectives, ils sont alors tous deux irrationnels.

très importante car les deux biais ne jouent pas le même rôle dans l'accès au financement. Aussi, je présente les conséquences de la confusion éventuelle de ces deux notions.

Les principaux résultats de ce chapitre suggèrent que la surconfiance des entrepreneurs empêche leur stigmatisation tandis que l'optimisme seul, ne l'empêche pas. Dans le modèle développé dans ce chapitre, un investisseur a le choix entre deux projets: celui d'un entrepreneur novice et celui d'un entrepreneur expérimenté qui a échoué auparavant. La principale différence entre ces deux choix est l'historique des entrepreneurs. Par conséquent, il y a stigmatisation si l'investisseur affiche une préférence pour le projet du nouvel entrant ¹¹. Lorsque la perception négative de l'échec est modérée (mais non positive), si l'entrepreneur est surconfiant, il n'y a pas de stigmatisation observable de l'échec. Cela s'explique par le fait que les entrepreneurs surconfiants réclament moins de parts que les entrepreneurs réalistes ou optimistes, afin de tenir leurs engagements. Ainsi, la surconfiance réduit la "rente d'agence" et les investisseurs profitent de cette situation pour extraire davantage de profit. Il en résulte alors une préférence pour les entrepreneurs surconfiants, y compris pour ceux qui ont expérimenté l'échec auparavant. En revanche, il n'y a pas de préférence pour les entrepreneurs optimistes qui ne font que surestimer les chances de succès, indépendamment de leurs efforts. Par conséquent, les entrepreneurs optimistes n'ont pas plus d'incitations à fournir des efforts, ou à tenir leurs engagements, que les entrepreneurs réalistes.

En pratique, il est difficile de reconnaître les entrepreneurs simplement optimistes et ceux qui sont surconfiants. Il n'est donc pas surprenant d'observer une confusion entre les deux biais. Néanmoins, le fait de confondre les entrepreneurs optimistes et ceux surconfiants a plusieurs répercussions. Tout d'abord, en raison de cette confusion, les entrepreneurs optimistes peuvent avoir un accès facilité au financement malgré d'éventuelles perceptions négatives de l'échec. Deuxièmement, puisqu'ils se verront proposer un contrat conçu pour les entrepreneurs surconfiants, ils se sentiront tout de même stigmatisés en raison de la faible rémunération qui leur est proposée. Enfin, le fait d'être moins incité à fournir des efforts, risque d'augmenter la probabilité d'échec. Ainsi, la confusion entre l'optimisme et

¹¹En effet, du point de vue de la qualité des projets ou du potentiel des entrepreneurs, il n'y a aucune différence. Cela signifie que l'investisseur devrait être indifférent entre les projets des deux types d'entrepreneurs.

la surconfiance conduit les investisseurs à financer des projets à valeur actuelle nette (VAN) négative.

Il ne s'agit pas de la seule situation où les investisseurs financent des projets à VAN négative. Bien que les croyances subjectives des investisseurs n'affectent pas le contrat optimal, elles sont essentielles à la prise de décision. L'optimisme des investisseurs peut également les conduire à financer des projets à VAN négative, tandis que les investisseurs pessimistes manqueront des projets à VAN positive. Plus important encore, lorsque les investisseurs sont optimistes, la surconfiance entrepreneuriale favorise le financement excessif de projets à VAN négative. Par conséquent, lorsque la surconfiance entrepreneuriale est prédominante, il est socialement plus souhaitable d'avoir des investisseurs réalistes ou même pessimistes. Au contraire, la surconfiance entrepreneuriale serait un remède au sous-financement des bons projets par les investisseurs pessimistes.

Par ailleurs, lorsque les investisseurs n'ont pas de croyances négatives sur l'échec, la stigmatisation n'apparaît que sous une forme subjective. C'est essentiellement le cas des entrepreneurs qui manquent de confiance en eux. En raison du niveau élevé de la rente d'agence liée au manque de confiance, ce type d'entrepreneurs n'obtient pas de financement. Cependant, la raison sous-jacente n'est pas due à la perception de l'échec par les investisseurs. Ainsi, il n'y a pas de stigmatisation de l'échec d'un point de vue objectif. Néanmoins, du point de vue subjectif des entrepreneurs ayant échoué, une telle décision peut être perçue comme une stigmatisation. Lorsque l'investisseur survalorise l'acquisition de connaissances par l'expérience ou l'apprentissage par l'échec, cette stigmatisation subjective est moins susceptible d'apparaître. En effet, comme les investisseurs valorisent l'expérience passée, les entrepreneurs ayant échoué, bien que peu confiants, ont plus de chances d'obtenir un financement que les nouveaux entrants. Dans ce cas, ni les entrepreneurs rationnels ni les entrepreneurs surconfiants ne sont stigmatisés.

Ainsi, ce chapitre propose deux façons d'échapper à la stigmatisation de l'échec. Premièrement, les investisseurs doivent accorder suffisamment d'importance à l'expérience. Deuxièmement, les entrepreneurs devraient conserver leur surconfiance même après un échec. En adoptant une approche novatrice de l'analyse de la stigmatisation de l'échec, ce chapitre

contribue à la littérature financière comportementale et entrepreneuriale. Bien qu'à prime abord, la surconfiance puisse être préjudiciable aux entrepreneurs en raison de la faible part qu'ils reçoivent, elle a des effets positifs sur l'accès au financement. En ce qui concerne les prédictions empiriques, ce chapitre établit que les entrepreneurs optimistes et surconfiants sont plus à même d'obtenir un financement pour des entreprises créées ultérieurement à un échec par rapport à ceux qui sont réalistes ou ceux qui sont devenus sous-confiants. Si la distinction empirique entre les deux biais devient possible dans de futures recherches, la probabilité d'échec observée devrait être plus importante pour les entrepreneurs optimistes. Enfin, les conditions économiques ayant une influence sur les perceptions, elles sont également en jeu dans l'accès au financement. Les périodes d'expansion économiques devraient être moins sujettes à la stigmatisation de l'échec et les échecs liés aux périodes de récession devraient être moins stigmatisés.

Le dernier chapitre de cette thèse traite également de la réintégration sur le marché entrepreneurial. Il questionne notamment l'existence d'une culture de l'expérimentation aux Etats-Unis ainsi que la contribution des capital-risqueurs à une telle philosophie. En effet, si *"l'entrepreneuriat est fondamentalement une affaire d'expérimentation"* (Kerr et al., 2014), les entrepreneurs ne devraient pas rencontrer beaucoup de difficultés pour se relancer et recréer des entreprises. Ils devraient être encouragés à implémenter de nouvelles idées, quels que soient les résultats de leurs expériences passées. L'échec étant un événement bien plus commun que le succès pour les entrepreneurs, il est essentiel de comprendre comment ce dernier est effectivement perçu dans un tel contexte. De manière générale, les États-Unis ont la réputation d'avoir une vision plus positive vis-à-vis de l'échec comparé à de nombreux pays européens où celui-ci est perçu négativement, voire même stigmatisé. En ce qui concerne l'échec entrepreneurial plus précisément, alors que ce dernier constitue une barrière à l'élancement dans l'entrepreneuriat en Europe (Cahn et al., 2021), des anecdotes laissent entendre que l'échec est tout autant valorisé que le succès aux États-Unis. Cependant, il faudrait s'assurer que cette perception positive de l'échec ne renvoie pas qu'à quelques exemples de réussites futures, souvent mises en avant. Une telle situation supposerait, de fait, qu'une part importante des échecs est négligée. Aussi, étant donné que les entrepreneurs

ont besoin de capitaux pour expérimenter, l'attitude des investisseurs à l'égard de l'échec nécessite d'être analysée de plus près.

Parmi les intermédiaires financiers, les capital-risqueurs sont particulièrement intéressants à étudier dans ce contexte. En effet, l'implication active de ces derniers dans les entreprises qu'ils financent les distingue des autres financiers. Outre cela, ces investisseurs sont également connus pour leur méthode spécifique d'infusion de capital : le financement par étapes. Les capital-risqueurs injectent des fonds aux jeunes entreprises au fur et à mesure plutôt qu'en une seule fois. Ils conditionnent le financement futur à l'accomplissement de certaines étapes importantes. Selon les signaux émis par les entreprises, entre temps, ils mettent fin à certains investissements afin d'alimenter davantage les entreprises les plus prometteuses. Cela leur permet d'investir initialement dans plusieurs entreprises et de donner une chance à de nombreux entrepreneurs. De ce point de vue, les investisseurs en capital-risque contribuent à l'expérimentation. Toutefois, se pose la question de savoir s'ils facilitent l'expérimentation essentiellement pour les nouveaux entrants, ou s'ils contribuent à la réinsertion des entrepreneurs expérimentés également ? Plus précisément, comment évaluent-ils l'expérience entrepreneuriale passée ?

Afin de répondre à ces questions, mon étude se focalise sur l'entrepreneuriat en série aux États-Unis et compare les primo-entrepreneurs à ceux qui en sont à leur deuxième création d'entreprise. Mes résultats soutiennent l'existence d'une vision de l'échec tant positive que négative. Dans un premier temps, j'analyse la probabilité de créer une nouvelle entreprise après avoir vécu un échec entrepreneurial. D'après les résultats obtenus, une telle expérience diminue la probabilité de se relancer dans l'entrepreneuriat par rapport à ceux qui ont connu le succès la première fois. De plus, conditionnellement à l'entreprise d'une nouvelle activité, ceux qui ont échoué auparavant s'avèrent plus susceptibles de changer d'Etat ou même de pays. Bien que ces résultats n'établissent pas de lien de causalité entre la perception négative de l'échec et l'incitation à se relancer dans une nouvelle création, ils incitent à explorer ce qu'il en est du point de vue de l'accès au financement.

Ainsi, dans un deuxième temps, je m'intéresse à la probabilité de lever des fonds de capital-risque et aux éventuelles différences entre les primo-entrepreneurs et les en-

trepreneurs en série. Un premier constat est que l'expérience entrepreneuriale préalable augmente la probabilité d'avoir un financement par capital-risque s'il s'agit d'une expérience réussie. En ce qui concerne les échecs passés, l'étude globale de l'entrepreneuriat en série révèle que l'échec n'est ni stigmatisé, ni valorisé. Cependant, ces résultats doivent être considérés avec prudence. En effet, une étude plus approfondie des entrepreneurs en série indique qu'ils ne sont valables que pour certains types de fondateurs d'entreprises. Si certains bénéficient d'une perception positive de l'échec, ce n'est pas le cas pour d'autres. Mes analyses soulignent que ce qui importe pour obtenir un financement par les capital-risqueurs, c'est l'expérience de financement par capital-risque et non l'expérience entrepreneuriale seule. Les entrepreneurs en série qui ont obtenu un financement par capital-risque dans leur entreprise précédente ont plus de chances de lever des capitaux dans l'entreprise focale, indépendamment de leurs résultats passés. À l'inverse, pour ceux qui n'ont jamais eu ce type de financement, l'expérience passée, y compris réussie, n'augmente pas la probabilité d'obtenir un financement par capital-risque par rapport aux nouveaux entrants. Au contraire, les échecs passés réduisent cette probabilité. Par conséquent, mes résultats laissent entendre que, même aux États-Unis, les échecs peuvent être pénalisés. Reste à comprendre si cela peut être qualifié de stigmatisation ou si les capital-risqueurs ont des raisons rationnelles de traiter différemment cette catégorie d'entrepreneurs.

Pour cela, j'étudie et compare les performances futures de ces deux groupes d'entrepreneurs en série. La préférence pour ceux qui ont déjà bénéficié d'un financement par capital-risque peut s'expliquer par la volonté de réduire les problèmes informationnels, grâce aux relations existantes avec le capital-risque. Néanmoins, il est important de comprendre si un tel choix est justifié du point de vue de la performance. De plus, des explications directement liées à la performance-même pourraient être également en jeu et nécessitent une certaine attention. Tout d'abord, tout comme les capital-risqueurs contribuent à la performance des entreprises qu'ils financent (Hellmann and Puri, 2002, Hsu, 2006, Sørensen, 2007, Bottazzi et al., 2008, Chemmanur et al., 2011, Bernstein et al., 2016, Ewens and Marx, 2018), ils pourraient aussi contribuer aux entrepreneurs. Si les entrepreneurs apprennent des capital-risqueurs, ces derniers pourraient avoir davantage confiance dans la capacité des

entrepreneurs à acquérir de leur expérience. Ainsi, cela expliquerait leur préférence pour ceux qui ont déjà intégré leur cercle. Ensuite, ce groupe d'entrepreneurs en série pourrait être plus attractif en raison d'un profil particulièrement représentatif de ceux qui ont réussi. Étant donné qu'ils ont déjà été sélectionnés par les investisseurs précédents, les futurs investisseurs peuvent s'appuyer sur ce premier filtre pour leur propre sélection des entrepreneurs en série.

Globalement, mes résultats révèlent que les entrepreneurs ayant une expérience antérieure du financement par capital-risque ne sont pas plus performants que les autres. Ainsi, les explications axées sur la performance sont rejetées. Les fonds de capital-risque semblent donc favoriser les entrepreneurs ayant déjà bénéficié d'un financement auparavant principalement en raison de leur processus de sélection. En effet, cette sélection s'appuie sur des critères prédéfinis qui réduisent les différences entre les profils qu'ils sélectionnent. En procédant ainsi, les capital-risqueurs diminuent également leurs chances de découvrir de nouveaux déterminants du succès et de se rendre compte qu'avoir eu un financement de capital-risque antérieurement n'est pas nécessairement un signal fiable. En outre, si cette étude confirme que le succès entraîne le succès (Gompers et al., 2010), elle ne dévoile aucun effet positif ou négatif de l'échec sur le succès futur. Du point de vue de la performance, il n'y a donc aucune raison de privilégier les nouveaux entrants à ceux qui ont échoué et vice-versa. De fait, toute préférence pour les nouveaux entrants par rapport aux entrepreneurs ayant échoué peut-être qualifiée de stigmatisation de l'échec.

Ce dernier chapitre met en avant des résultats qui ont d'importantes implications tant pour les entrepreneurs que pour les investisseurs. En effet, il révèle que, même aux États-Unis, démarrer une nouvelle entreprise après un échec est loin d'être évident. Plus précisément, bien que l'existence d'une perception positive de l'échec soit confirmée par cette étude, elle établit également que l'échec peut être malgré tout stigmatisé dans certaines situations. Cependant, il s'avère que les deux types de perceptions sont inappropriées. Si les conclusions de ce chapitre soutiennent que l'échec ne doit pas être stigmatisé, elles indiquent également qu'il ne doit pas être surestimé. Les entrepreneurs qui ont échoué, en moyenne, ne semblent pas tirer de leçons de leurs expériences passées. Toutefois, les capital-risqueurs

adoptent les deux visions erronées à la fois. Premièrement, ils encouragent l'expérimentation pour ceux qui ont déjà obtenu un financement par capital-risque dans le passé, en surévaluant leur expérience. Deuxièmement, ils limitent l'expérimentation pour ceux qui n'ont jamais eu accès au financement par capital-risque, en stigmatisant l'échec. Cependant, ce dernier groupe d'entrepreneur en série est plus performant que le premier. Il existe donc de précieuses opportunités d'investissement en dehors du champ de vision des capital-risqueurs.

Chapter 1

From In-Person to Online: the New Shape of the VC Industry

with

Liudmila Alekseeva (IESE Business School),

Silvia Dalla Fontana (USI Lugano and SFI),

and Hedieh Rashidi Ranjbar (University of Michigan Ross)

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Abstract

Geographical clustering is an essential feature of the venture capital (VC) industry as proximity helps VCs to acquire soft information about early-stage companies and to conduct post-investment activities. However, whether the VC investment model based on in-person interactions is still justified in the age of online communication technologies remains an open question. This chapter addresses this question by using an unexpected interruption in face-to-face meetings during the recent pandemic. We document that VCs respond to this change by breaking their traditional norm: they invest in more distant startups. We find that this evolution goes along with selection criteria and syndication process changes. Overall, online interactions do not seem to provide VCs the soft information they used to have and which appears still crucial for them. Thus, our study helps to understand how VCs revisit their investment model and sheds light on the value of in-person interactions for the VC industry.

1.1 Introduction

“I think the biggest challenge is the inability to go visit somebody, to walk around their office, to get a feel for their culture”

Roelof Botha, VC at Sequoia Capital

Active involvement with their investments sets venture capital (VC) investors apart from the typical financial intermediary. These investors not only provide startups capital but also support them through multiple post-investment services (Gorman and Sahlman, 1989, Lerner, 1995, Hellmann and Puri, 2002, Gompers et al., 2020). Because VC investors invest in early-stage companies about which little information is available, they have to rely on soft information about their investment targets. This type of information cannot be easily summarized by a numeric score and reliably transferred through distance (Petersen and Rajan, 2002). Therefore, in-person interactions have been perceived as crucial in the VC industry both for the selection process and post-investment activities (Bernstein et al., 2016). In fact, to accumulate and exchange soft information, VCs spend much of their time networking (Gompers et al., 2020) and locate in entrepreneurial clusters facilitating frequent face-to-face interactions (Sorenson and Stuart, 2001). Nevertheless, the literature has not yet explored if in-person interactions are an essential feature of the VC investment model or simply a result of historical norms.

One way to answer the question about the importance of in-person interactions for the VC industry is by studying the consequences of a restriction on such interactions. In this chapter, we exploit the sudden interruption of in-person communication due to the recent pandemic to explore changes in VC investing when all face-to-face communication is replaced by online meetings.

Even though online interactions might be a good substitute for in-person ones, they seem imperfect. Roelof Botha, a VC at Sequoia Capital, one of the largest VC firms in the United States, recently reported: *“I think the biggest challenge is the inability to go visit somebody, to walk around their office, to get a feel for their culture”*¹. Thus, we describe changes in VCs’ behaviors around an event that stressed the traditional norms of the VC industry.

We provide evidence on how a change in soft information collection from in-person to online impacted the behavior of these active financial intermediaries. We start by investigating whether

¹From *McKinsey on startups* podcast. See <https://www.mckinsey.com/industries/technology-media-and-telecommunications/our-insights/global-vc-view-funding-startups-in-the-next-normal>.

the geography of the VC investments is transformed with the arrival of the Covid-19 outbreak. As it is more difficult and costly to communicate with distant parties, distance has been perceived as an important barrier to soft information collection (Petersen and Rajan, 2002, Agarwal and Hauswald, 2010). Since the pandemic-related restrictions forced investors to interact with all firms in the same way, i.e., online, the gap in the quality of soft information and the cost of its collection between proximate and distant companies was reduced. Therefore, we can expect VCs to break their traditional investment model and invest in more distant startups. Also, by replacing face-to-face interactions with online meetings, the pandemic might have changed the type of soft information that VCs can collect about early-stage companies². Thus, we explore if changes in interactions and information collection lead VC investors to revise their requirements about their portfolio companies' characteristics and to adjust their syndicate's structure. For our analysis, we use data on VC investments in the United States from VentureXpert and Pitchbook datasets.

We first focus on the distance between VC investors and their portfolio companies. One main consequence of the new environment imposed by Covid-19 is that physical distance has become less constraining, since all firms, whether very close to each other or not, are now interacting similarly: online. As the collection of soft information is no more facilitated by proximity, we expect the distance between VC investors and their portfolio companies to increase post-pandemic. Although the timing of the Covid-19-related restrictions within the United States does not help us to make causal claims³, we document that in a cross-section of all VC first-round investments, the distance between a VC firm and its portfolio company increases by 43%. When looking at the variation within a VC firm, the distance still increases by 27%. Our findings suggest that this increase in distance also translates into VCs being more likely to invest outside their state borders. We observe that VCs are 15% less likely to invest in their own state. We additionally notice that this increase in distance reflects some redistribution of the number of VC investments from large entrepreneurial hubs (i.e., San Francisco, San Jose, Boston, or New York) toward non-hub areas. VCs located in hubs are less likely to invest in hub companies after Covid, while VCs located outside hubs are equally likely to invest in hubs before and after.

²VCs respond strongly to information about the founding team (Bernstein et al., 2017) and make investment decisions based on gut feelings and personal bonds with entrepreneurs (Hu and Ma, 2021, Gompers et al., 2020).

³Since most U.S. states introduced Covid-19-related restrictions in March 2020, we do not observe enough variation in restrictions across states to exploit them empirically.

It is also relevant to consider that Covid-19 not only transformed the way firms do business but also significantly impacted the economy overall. This is why in our analysis, we try to exclude the explanation that VCs invest in distant states because these areas house industries that suffered less or even benefited from the pandemic. In that case, the increase in distance would only be a consequence of a higher focus on specific industries. We control for the change in the industries' and states' growth rates, and we do not find evidence supporting this alternative explanation. Then, we also ensure that the increase in distance is not driven by the emergence of new businesses in states that are far away from the usual clusters. We thus exclude this alternative hypothesis by controlling for the change in the growth rates of states' business applications before Covid. Lastly, we exclude the possibility that VCs invest farther away due to the high amount of capital they have on hand by controlling for the total amount of capital raised by VC funds at the analyzed investor's location in all distance-related regressions.

Our findings regarding distance raise further questions about the necessity of in-person interactions to collect soft information. Do these results suggest that VCs do not need such interactions to gather the information they used to have? Or do VCs find a way to balance the limited access to this information? To answer these questions and to understand how VCs respond to the lack of in-person due diligence, we examine changes in portfolio companies' characteristics. If in-person interactions are not essential to acquire soft information, we should not observe significant differences before and after Covid. In addition, now that the cost of information collection for distant and close firms is similar, we expect features of distant investments observed before the pandemic to be less noticeable post-pandemic. Thus, we first test if the average portfolio companies' age change and if VCs try to impose stricter control over portfolio companies. The portfolio company's age was shown to increase in distance (Sorenson and Stuart, 2008), consistent with the idea that older companies may have more hard information, such as financial records. Also, VCs used to appoint fewer board members in more distant companies (Lerner, 1995). We find that post-pandemic, VCs start investing in more mature firms and on average appoint fewer board members, even in proximate companies. These findings suggest that investments made after the pandemic resemble typical distant investments. Hence, online interactions do not seem to fully substitute for in-person ones and to overcome frictions traditionally associated with distance.

In addition, our results show that startups receiving VC financing post-pandemic are no more likely to have a pre-VC financing round. At the same time, company valuations are not significantly different post-pandemic after controlling for overall VC funds' inflows (as the competition among VCs could push valuations up and push VCs to offer better deals (Hochberg et al., 2007)).

We then investigate if VCs change the way they invest in syndicates, as a balancing mechanism to the change in their information environment. Syndication not only helps share risk but also enables VCs to bring together more expertise and insights on investment opportunities (Lerner, 1994). Therefore, we expect VCs to reach out to other funds more in a period with lower availability of information and overall higher uncertainty. Indeed, we find that post-Covid, VCs are up to 13% more likely to engage in syndicated deals. We also observe that the average distance across syndicate members increases, as does the probability of investing with old syndicate partners. Besides, a syndicate is more likely to have at least one VC specialized in the company's industry. These results are coherent with a post-pandemic information environment becoming more challenging and with VCs leveraging their network in a crisis.

Lastly, we provide some early insights into the performance of VC investments that were deal-sourced online rather than in-person. Due to the limited time that passed from the start of the pandemic, we first focus on the probability of raising a second financing round as a primary performance indicator. Our preliminary findings reveal that there is not a statistically different likelihood of having a second VC round within 6 months for companies that received their first round after Covid, compared to the ones that received their first round before. However, when looking at the probability of getting a second round within 12 or 18 months, companies that received their first round after Covid appear more likely to obtain a second round, compared to those that received their first round before Covid. We then focus on the probabilities of companies to go public or to get acquired within 18 months since their first VC investment. Our exit-related results show that so far companies that received their first VC round after Covid are not less likely to exit fast - within 18 months. Due to a very short time available to observe exits or second round data for companies that received VC financing post Covid, these results should be interpreted with caution. Further explorations of data covering a more extended post-Covid period will enable us to shed light on how critical in-person interactions are for the performance of VCs' deal sourcing and post-investment activities. This, in turn, could indicate whether the traditional VC due diligence model based on in-person interactions delivered better quality investments than remote investing.

This chapter contributes to different strands of literature. As soft information is a key driver of VCs' investment decisions, our study is strongly related to this literature (e.g., Petersen and Rajan, 2002, Stein, 2002, Liberti and Petersen, 2018). We attempt to provide an early performance analysis to assess how crucial soft information collected in person is for the VC industry. We also contribute to understanding how VCs adapt their selection and syndication processes when broadening their horizons in an unfamiliar environment, where access to the soft information they used to collect is constrained. Indeed, our results suggest that VCs might try to compensate for the inability of in-person due diligence by investing in more mature startups and leveraging their syndication networks. Although we observe that VCs changed their investment behavior, our findings suggest that they remain cautious and make small vigilant steps toward a new model. Our study also adds to the literature on the geography of the VC industry (e.g., Sorenson and Stuart, 2001, Bengtsson and Ravid, 2009, Chen et al., 2010, Cumming and Dai, 2010). It reveals that while communication technologies long ago created the opportunity to change the traditional VC investment model based on geographical clustering and in-person communication, the restriction of in-person activities during the Covid-19 pandemic accelerated this change. Our findings show a sharp increase in distance between investors and their portfolio companies that does not revert back even after the restrictions on in-person interactions are removed. Finally, by analyzing the change in the VCs' behavior around the unexpected arrival of the pandemic, our study contributes to a growing literature on the impact of Covid-19 on entrepreneurship and the VC industry (e.g., Howell et al., 2020, Gompers et al., 2021).

Our results have a range of important implications. First, switching from in-person to online communication seems to induce VCs to reconsider the need for strong geographical clustering with their portfolio companies. This finding has potential implications for the diffusion of entrepreneurial activity and innovation spillovers outside traditional hubs. As VCs expand the geography of their investments, the importance of traditional few clusters of innovative entrepreneurship might decrease, allowing for the growth of new hubs and the diffusion of valuable human capital. Second, we observe that the characteristics of startups selected online are more similar to characteristics traditionally associated with distant investments. Thus, VCs seem to be more cautious when choosing companies for online investment, even if they are located nearby. This result suggests that online interactions might not allow VCs to collect soft information that they used to collect via in-person networking. Finally, we observe that VCs seem to leverage their

networks more than before. This might be an important mechanism of information transfer when face-to-face meetings with the startup team are not possible. VCs reach to more remote and to trusted prior partners, they include an industry expert in the syndicate, and despite that distance to investments increases, VCs still ensure that at least one syndicate's VC is located in the vicinity of the company. These results have implications for the evolution of VC networks, because if VCs find it more crucial or easier to engage with their peers, the role of networks is likely to increase. Overall, these adjustment mechanisms suggest that even with evolving information technologies, it is impossible to perfectly replace soft information through online communication, and that the VCs' behavior is sticky. Thus, we should not expect soon dramatic changes in this industry, such as investments in rural areas or in substantially different startups characteristics.

The remainder of the chapter is organized as follows: after reviewing the related literature in Section 1.2, we describe the data in Section 3.2, while Section 1.4 exposes our estimation strategy. Section 1.5 describes the new geographical scope of the VC industry. Section 1.6 addresses our main concerns related to alternative explanations while changes in investment characteristics and syndication process are detailed in Section 1.7. Finally, we provide preliminary insights on performance in Section 1.8 before concluding with Section 1.9.

1.2 Literature review

This chapter first contributes to the literature analyzing the role of soft information in financing decisions (e.g., Petersen and Rajan, 2002, Stein, 2002, Liberti and Petersen, 2018). The need to rely on soft information is not unique to the VC industry; indeed, it is typical to all industries characterized by the lack of hard information. The VC setting is particularly well suited to study this area, as soft information is quite important in less hierarchical organizations (Stein, 2002, Berger et al., 2005), which is the case of VCs and startups. A recent review of the literature, Liberti and Petersen (2018) show that distance is linked to the type of information available to financial intermediaries. Soft information is private, non-verifiable, and difficult to summarize, so it can hardly be transmitted without losing content. Hence, distance can be a significant barrier to collecting this type of information. Our study contributes to this literature by documenting the behavior of financial intermediaries, i.e., VCs in our setting, when they are forced to change the way they collect information about their investment opportunities. Early evidence from Petersen

and Rajan (2002) shows that distance in small business lending, another sector characterized by the lack of hard information, has been increasing over the past decades, thanks to improvements in information technology. We document that VCs as well increase the distance to their investments when the benefit of easier communication with proximate companies is removed.

By showing an increased willingness of VCs to invest in distant companies, our study also adds to the literature on the geography of the VC industry and, in general, of all industries that particularly need to rely on soft information for their financing decisions. Until the Covid-19 onset, VCs were known to be geographically concentrated and to invest in companies close to their headquarters (Sorenson and Stuart, 2001, Bengtsson and Ravid, 2009, Chen et al., 2010, Cumming and Dai, 2010). We show that the need to move to online meetings changed the geographic shape of VCs' investments, and we try to understand the underlying mechanisms and consequences of such a change. As stated by Sorenson and Stuart (2001), VCs' geographical and industry concentration are closely related to their pre- and post-investment activities. Indeed, identifying and evaluating opportunities is believed to be easier when searching locally. Considering the opacity of the private market, VCs rely essentially on soft information since hard information is not much available for new ventures. Therefore, communicating with all the parties of a firm or obtaining more information from local media or even other ties with local executives is extremely valuable and justifies the preference for local investments (Cumming and Dai, 2010). While characteristics about the type of information that can be collected for investment decisions by VCs are also common in other industries that lack hard information, the type of financing provided to startups makes the VC post-investment activities a specific feature of this industry. VCs interact with the companies they invest in by monitoring and advising them, all activities that are easier when the portfolio company is not far away (Bernstein et al., 2016).

Also, the geographic concentration of VCs is not random at all. Chen et al. (2010) show that VCs locate in regions known to host highly successful VCs. Interestingly, they stress that VCs' outperformance in such areas comes mainly from their non-local investments. The authors believe that a potential explanation for this is a higher expected rate of return for distant investments, which implies higher monitoring costs. At the same time, we know from Cumming and Dai (2010) that VCs who are less subject to local bias are more reputable VCs or those with broad networks, i.e. those with a higher likelihood of success (Hochberg et al., 2007). The importance of the network for distant investments, apart from experience, is also highlighted by Sorenson and Stuart

(2001), who show that such investments are more frequent for VCs who have multiple and dispersed relationships with other investors as this increases the likelihood of finding a co-investor who is closer to the distant target. Nevertheless, social networks also tend to cluster geographically, and stronger ties will emerge with nearby investors, reducing the probability of investing too far (Sorenson and Stuart, 2001, Hochberg et al., 2007). Interestingly, our study shows that the increase in distance between investors and targets goes along with an increase in distance between the syndicate members as well, and VCs become more likely to co-invest with known syndicate parties. Hence, we contribute to learning more about the new composition of the VC syndicates and interpret our results in light of Hochberg et al. (2010) findings. This latter emphasizes the difficulty of entering a local VC market due to solid networks. The authors show that incumbents are reluctant to invest with new entrants as this may reduce their probability of being invited into their fellow incumbent's syndicates. Moreover, prior tie density is identified as a critical element for forming a syndicate (Zhang et al., 2017).

The literature provides further evidence about the peculiarities of distant investments that we also analyze under the Covid-19 context. Lerner (1995), for instance, finds that the number of board members decreases with distance as the oversight of distant firms is more costly than that of local businesses. Bengtsson and Ravid (2009) show that Californian startups benefit from more entrepreneur-friendly contracts and suggest that contracts should be more investor-friendly with distance. Tian (2011) indicates that VCs located farther away from their portfolio companies prefer to invest smaller amounts through a larger number and closer-timed financing rounds. Regarding the valuation of companies, different dynamics may be at play and need to be considered. Since distant investments imply greater information asymmetry and uncertainty, VCs may demand a higher premium. This is even more true if competition among VC investors is high (Gompers and Lerner, 2000). However, Casamatta and Haritchabalet (2007) also explain that syndication is essential to prevent competition between investors. In addition, Hochberg et al. (2010) point out that companies located in densely networked markets are valued less highly. Therefore, if distant investments assume more syndication, we should expect less competition among investors and lower valuations for the portfolio companies. We analyze a range of VC investment characteristics along the lines of prior literature and show that, after the restrictions on in-person communication are placed, VCs adjust selection criteria for their portfolio companies. Overall, portfolio companies selected online rather than in-person are somewhat more similar to remote companies in the pre-

pandemic period.

Because we exploit the setting in which interactions were not entirely eliminated but forcefully transferred to the online world, we also speak to the literature analyzing the role of information technologies for collaboration. By reducing communication costs, the adoption of the Internet⁴ played an essential role in new collaborations. In academia, for instance, it positively affected the productivity and the expansion of collaborative networks (Agrawal and Goldfarb, 2008, Ding et al., 2010). Moreover, these studies highlight the “equalizing force” of IT with a more pronounced effect on middle-tier universities, women, and scientists from non-elite institutions. Nevertheless, there is no consensus about the geographical shape of collaborations even though it is well established that the Internet reduced the importance of distance (Forman et al., 2005). Agrawal and Goldfarb (2008) find that collaboration increased across institutions but in the same region. At the same time, Forman and Zeebroeck (2012) argue that research teams in geographically dispersed firms collaborate more after the diffusion of the Internet, while the same result is not observed within the location or for single inventors. Our findings concerning distance among syndicate members in the VC industry support the latter view.

Finally, our study contributes to the rich literature on the Covid-19 pandemic while being specific to venture capital and entrepreneurship research. Howell et al. (2020) and the Gompers et al. (2021) survey provided the first insights into how this crisis affected VCs’ activity. As observed in previous recessions, Howell et al. (2020) confirm the strong sensitivity of early-stage VC investments to market conditions. They report a decline in early-stage activity by 38% during the first two months of the pandemic, while late-stage VC activity did not change. Gompers et al. (2021) support that the overall activity of the VC industry has been reduced less compared to previous recessions. Consistent with this finding, they notice that VCs are optimistic about their performance. Also, despite the increased difficulty in evaluating new opportunities, they observe little change in the split of VCs’ time between existing companies and the search for new ventures. Thus, according to these studies, the VC industry does not seem to exhibit significant changes in investment activity. Nevertheless, we find a major change in VCs’ behavior: their increased propensity to invest farther away. Han et al. (2022), the closest study to ours, also provides evidence about the increase in distant investments in various countries. Hence, this new investment behavior is not restricted to the US and seems to be a global phenomenon. By looking

⁴Most of the studies focus on BITNET, an early version of the Internet.

more closely at the composition of the VCs' portfolios, Bellucci et al. (2022) present additional support for the VCs' ability to respond to changing market conditions. Indeed, they show that VCs' portfolios contain more companies developing technologies that are useful for social distancing and pandemic issues. In line with prior research, they observe that those adapting the most to new market opportunities are older and more focused VCs (Gompers et al., 2008). We complement these findings by showing the change in the VCs' new investment selection criteria and the syndication process in the post-pandemic period.

1.3 Data

In this chapter, we use two major datasets on VC investments - Refinitiv and Pitchbook. The first data source we use is *Refinitiv's* venture capital investments database. We concentrate on investment rounds conducted by U.S.-based funds of U.S.-based venture capital firms. We include the first rounds of financing received by each portfolio company and classified as seed or early-stage. Our primary dataset includes investments made between April 2018 and December 2021, to have equal time periods before and after the Covid-19 onset.⁵ We only consider investments received by U.S.-based entrepreneurial companies. We exclude deals in which the names of venture capital firms or funds are not disclosed as well as deals for which the investment amount or other key information for the analysis is missing. We also eliminate deals with date incoherencies such as those for which the investment date is anterior to the founding date of the VC firm or of the portfolio company and those for which the company's founding date is after its IPO date. Our sample has 10,919 observations at the investor-startup level and includes 4,772 unique entrepreneurial companies financed by 2,474 unique investors. When considering only lead VC investors for each deal, we get 4,772 observations with 1,348 unique lead investors. Panel A of Table 1 presents descriptive statistics for the key Refinitiv-based variables used in the analysis, with each observation at the lead investor-startup level⁶. Finally, from Refinitiv, we also obtain VC fundraising data for U.S.-based funds to estimate a control for the VC capital available for investment at the state level.

⁵We consider the beginning of March 2020 as the period of the Covid-19 onset in the United States. This period was chosen based on when most U.S. states started imposing Covid-related restrictions.

⁶In our analysis, we also use the sample at the investor-startup level that includes all investors participating in the round. For this sample, the descriptive statistics are consistent with the ones presented in Table 1.

The second source of data for our analysis is *Pitchbook*. Pitchbook is probably the most comprehensive source for information about VC investment rounds. It provides information on deal characteristics, such as deal valuations and members of the board of directors, not available in our Refinitiv database. We implement the same filters as for Refinitiv to Pitchbook data. The time span of Pitchbook data is slightly shorter because we do not have data after June 2021. Therefore, the Pitchbook sample includes VC investments performed between November 2018 and June 2021. The resulting dataset contains 4,782 unique portfolio company investments from 1,219 unique investors. Panel B of Table 1 presents descriptive statistics for the key Pitchbook-based variables used in the analysis. From this table, we can see that the descriptive statistics of both datasets are coherent for most of the variables. However, the Pitchbook sample contains more seed round investments in percentage terms than the Refinitiv sample. This is likely to be due to different classifications of deal types in the datasets.

We supplement our VC investments data in several ways to study the potential effects of new businesses and industry changes due to the Covid-19 crisis. We use Compustat as well as two additional data sources introduced by the Census Bureau to provide granular, timely, and high-frequency information about the pandemic: the monthly Business Formation Statistics (BFS) and the Small Business Pulse Survey (SBPS).

The *BFS* provides business applications and formation time series at the national, state, and even industry level. The number of applications is obtained from the Internal Revenue Service (IRS) data based on Employer Identification Number (EIN) applications. Considering the importance of following fast-changing economic conditions, the Census Bureau made available weekly (starting from April 2020) and monthly data (starting from January 2021). Also, since the application process is mainly online and automated, new applications are processed almost immediately. Therefore, we use the monthly BFS data to construct different state-level measures. In the applications series, four categories of application numbers are reported: business applications (BA), high propensity business applications (HBA), business applications with planned wages (WBA), and corporations (CBA). As the HBA captures the likelihood to become an employer business ⁷, we use seasonally adjusted HBA to create our measures.

The *SBPS* data is a unique real-time survey of small employer businesses that started in April 2020, to track changing business conditions during the pandemic for small businesses. Single-

⁷Specific conditions based on industry, type of entity, the reason for application, and wage are used to identify a high propensity business application (HBA)

location small businesses (with less than 500 employees and revenue \geq \$1000) from the 2017 Census are targeted via e-mail. The survey comprises multiple phases ⁸ and it contains checkbox response questions. It starts with broad questions related to the overall effect of the pandemic on the business to introduce more detailed questions later on. It contains around 20 questions, and to make longitudinal analysis possible, from one phase to the other, consistency of the questions is ensured despite some little modifications. We use this survey to implement a control for industry growth across different states in our analysis. More details on the economic mechanism underlying the need to control for industry and how the variable is constructed are outlined in Section 1.6.

1.4 Estimation Strategy

1.4.1 Distance Analysis

In financial relationships involving small and opaque businesses (small business lending, venture capital, real estate), soft information plays a key role because hard information is often unavailable. Therefore, in-person interactions are crucial as they constitute an essential source of soft information collection. Since it is more difficult and costly to communicate with distant partners, distance is perceived as an important barrier to soft information acquisition (Petersen and Rajan, 2002, Agarwal and Hauswald, 2010). This explains why geographical clustering is frequent in industries that depend on soft information. However, with the adoption of new communication technologies, the collection and transmission of information changed. Online communications increased the availability of timely hard information and reduced the use of soft information in lending relationships. As a result, the distance between small firms and their lenders has been increasing for decades (Petersen and Rajan, 2002). Nevertheless, geographical clustering has persisted in industries like the VC industry, where hard information is lacking. Face-to-face and informal meetings have historically been a norm in the VC industry.

However, the Covid-19 pandemic created a strong unexpected stress on this norm by impacting the way people communicate. It interrupted all in-person meetings and introduced a widespread adoption of teleworking. Within March 2020, U.S. states' governments introduced unprecedented restrictions on people's movement and face-to-face interactions. Many states started by closing schools and canceling large public gatherings. Then, closures extended to workplaces, and all non-

⁸There are 8 phases by April 2022. See Buffington et al. (2020) for more details on the data.

essential workers were required to stay home. By the end of March, all U.S. states had introduced rather strict distancing measures and everyone who could, started working from home. Thus, many (if not all) business meetings were replaced by online meetings. The widespread switch to video communication services such as Zoom, Microsoft Teams, Skype, or other similar software can be observed in the soaring stock prices of their providers, reflecting how crucial web conferencing has become.⁹ One main consequence of such severe restrictions on movement and communication is that physical distance has become less relevant. All firms, whether very close to each other or not, were forced to interact in the same way: online.

Before the Covid-19 onset, soft information about proximate companies was more accessible compared to distant companies. VCs used to organize different events to meet founders and other investors to learn more about existing and potential investments. As distance is traditionally considered a major barrier to soft information exchange, the VC industry is characterized by high geographical clustering that persists even to date, while the large availability of IT communication significantly impacted other financial intermediaries such as banks. After the pandemic outbreak, proximity provided no more advantage for information collection. Hence, it reduced the gap in the quality of soft information and the cost of its collection between proximate and distant startups. We expect that, in such conditions, VCs would break the traditional norm and expand their investment horizons, looking for promising investments beyond the usual borders. To explore whether the average distance to portfolio companies changed in response to the restrictions on in-person interactions, we use the following specification:

$$Distance_{j,i,t} = \beta_1 Post\ Covid + X'\theta + \alpha_i + \omega_l + \gamma_s + \eta_v + \epsilon_{i,j,t} \quad (1.1)$$

The dependent variable is the logarithm of one plus the distance measured in kilometers between investor i and company j at time t . We use the latitude and longitude of investors' and companies' zipcodes to estimate distance between them. The main explanatory variable, *Post Covid* is a dummy that equals 1 if the financing round happened after February 2020, and zero otherwise. The vector of controls X includes the number of investors participating in the round, the natural logarithm of the round's equity investment amount, the natural logarithm of the total capital raised by VC funds in the VC's state lagged by one year¹⁰, and a dummy variable for

⁹For example, Zoom stock price grew from around \$100 in February 2020, to nearly \$560 in December 2020.

¹⁰We control for VC capital raised to ensure that the change in distance is not driven by competition between VC firms and limited local investment opportunities. See section 1.6 for further explanations.

whether the company is located in an entrepreneurship hub. The specifications also include the company's industry (α_i) and location state (ω_l) fixed effects, investment stage fixed effects (γ_s), and VC investor fixed effects (η_v).

1.4.2 Investment Characteristics Analysis

To better understand how the restrictions on in-person communication affected VCs' selection process and investment strategies, we analyze different investment characteristics at both the VC and the company levels. At the company level, we first focus on characteristics for which prior studies showed a relationship with distance, like the age of the company and the number of board seats appointed by the VCs (e.g., Lerner, 1995). We then explore at the VC level if the decrease in in-person interactions makes it harder for VCs to reach out to their networks or if the need to collect information about investment opportunities increases the inter-VCs relationships (Sorenson and Stuart, 2001). We study how different these characteristics are between pre- and post-Covid periods. In general, now that the gap between distant or proximate investments is reduced because both share the same means of communication (i.e., online), we can expect investments to look, on average, more similar to investments in proximate firms before Covid if online interactions are good enough substitutes to in-person interactions. Contrarily, we can expect investment characteristics post-pandemic to be more similar to those traditionally associated with distant investments if online and in-person interactions are not perfect substitutes. The remaining part of this analysis investigates changes in attributes that are more closely linked to the risk profile and bargaining power of the investors, such as the probability of the VC investor to select a company from outside of its focus industry and company valuations.

The following regression specification is used to analyze investment characteristics in the post-pandemic period and their relationship with distance:

$$\begin{aligned} \text{Investment Characteristic}_{j,i,t} = & \beta_1 \text{Post Covid} + \beta_2 \text{Distance}_{j,i,t} + X'\theta + \alpha_i + \omega_l \\ & + \gamma_s + \eta_v + \epsilon_{i,j,t} \end{aligned} \quad (1.2)$$

where the dependent variable takes the form of various characteristics of investment made by investor i in company j at time t . The main explanatory variables in this equation are *Post Covid* and $\text{Distance}_{j,i,t}$, where as before, *Post Covid* is a dummy that equals 1 if the financing round happened after February 2020, and zero otherwise; and $\text{Distance}_{j,i,t}$ is the natural logarithm of one

plus the distance between the investor and the startup measured in kilometers. Control variables and fixed effects are defined as in equation 1.1.

1.5 Investing across usual borders: the new shape of the VC industry

While VC investors highly value face-to-face interactions due to the lack of tangible information about the quality of young startups, the Covid-19 onset interrupted this routine. Startup demos, networking events and dinners with founders were no longer possible after the pandemic. VCs had to adopt videoconferencing as the primary tool to keep learning about investment opportunities, meet startup founders, and monitor portfolio companies. Collecting information about a neighboring startup became as complicated as collecting information about a startup located a thousand miles away. Therefore, we expect that the leveling out of communication with proximate and distant partners led VCs to expand their geographical investment horizons. When there is no benefit in focusing on local startups, a new investment opportunity from far away becomes at least as attractive.

Our results support this view and show a significant increase in more distant investments after the Covid-19 onset. Table 2 shows the results of our main specification, as in equation 1.1. In a cross-section of all VC investments (columns (1) and (2)), the coefficients of *Post Covid* are 0.409 and 0.355, suggesting that the distance between a VC firm and its portfolio company increased by between 43% and 51% on average. If we compare the distances “within” a VC investor’s portfolio (coefficient of *Post Covid* equals 0.261 in column (3)), the distance increased by 30%. Finally, when we additionally control for whether the portfolio company is located in an entrepreneurial hub ¹¹, the increase in distance post-Covid is still substantial: 27%. Thus, post-Covid, a VC investor selects companies located 27% farther away compared to its portfolio companies selected before the Covid-19 pandemic. Similar results are observed in Table A2 when using Pitchbook data at the lead investor-portfolio company level. Our finding is also robust to controlling for the seasonality of the VC investments by including month fixed effects (not reported). Figure 1 complements these results by showing how important the changes are in terms of distance range. Then, we test if VCs invest within their own state or if VCs also became more likely to invest across geographical borders. Table 2 underlines that VCs are 2.5% to 7.1% percentage points less

¹¹Unreported coefficient of the dummy variable for whether the company is located in San-Francisco, Boston, or New York City is negative and strongly significant

likely to invest inside their state (columns (5) and (6)). This represents a 5-15% decrease in the unconditional probability.

A question that remains open is whether these results are likely to show a permanent trend or whether the increase in distance is going to reverse when online-only interactions are no longer mandatory. Although the time series available post-pandemic is relatively short and does not allow conclusive claims, evidence on the first investment rounds up to the second half of 2021 (which includes a period where restrictions started being relaxed) suggests that the probability of investing outside the state borders does not revert to the pre-Covid period levels, as reported in Figure A1. Furthermore, data and surveys conducted by researchers on working from home in general¹² suggest that the changes in behavior implemented after the pandemic onset are lasting.

In a supplementary analysis, we explore what kind of VC investors drive this increase in distant investments. Sorenson and Stuart (2001) suggest that more experienced VCs are more likely to invest in more distant companies because they have larger networks with other venture capital firms, entrepreneurs, and professional services providers in various locations. We rerun our distance regressions, splitting the sample by the median experience of the VC firms. We measure experience as the total number of unique companies in which the VC invested by 2018 (a year before the observation period starts). Table A3 in the Appendix shows that the coefficient of *Post Covid* is positive, strongly statistically significant, and is larger for less experienced VC firms, in the cross-section and in specifications with VC firm fixed effects. Thus, the increase in distance seems to be primarily driven by less experienced VCs who, on average, are more sensitive to distance (Sorenson and Stuart, 2001). Our results are robust to different measures of experience.

Does this increase in distance reflect the reallocation of VC investments from established entrepreneurial hubs towards other locations post-Covid? If participating in the typical in-hub activities such as networking events and informal gatherings had some value, we expect that post-pandemic, as companies located in an entrepreneurial hub could no longer benefit from this competitive advantage, the probability of selecting a portfolio company located in a hub is lower. We address this question by looking at the likelihood that the portfolio company is located in the state of California or one of the entrepreneurial hubs (i.e., San-Francisco, Boston, New York). Table 3 shows that in the cross-section, there is a statistically significant redistribution of the number of investments from hubs toward other areas (columns (1) and (3)). After Covid, the

¹²See Barrero, Bloom and Davis data project: <https://wfhresearch.com>

portfolio company is 5.8 percentage points less likely to be located in the state of California and 6 percentage points less likely to be in the entrepreneurial hub's metropolitan area. When we analyze investments with VC fixed effects, i.e., "within" VCs' portfolios, we can observe that once everything moved online, a VC investor is 4 percentage points less likely to invest in a company based in San Francisco, Boston, or New York (while the coefficient for the probability to invest in California-based company is negative, it is not statistically significant). This change represents a 7% decrease in the unconditional probability of investing in a hub-based company.

We next explore whether VC firms located in and outside entrepreneurial hubs behave differently with respect to whether they choose companies located in or out of hubs. For this purpose, we split our sample based on the lead VC firm's location in or out of large entrepreneurial hubs (i.e., San Francisco, Boston, or New York). Table 4 shows that in-hub VC investors are those responsible for the decrease in the proportion of portfolio companies located in hubs. Lead VCs located outside the hubs do not seem to change their preference for in-hub or out-hub portfolio companies. Therefore, we might see evidence of the redistribution of the VC investments from hubs toward non-hub areas. This is consistent with Han et al. (2022) who find that, the share of investments in the areas that received less VC financing before Covid, increased after Covid. Here, we add to this evidence by showing that it is due to VCs located in hubs.

In an additional analysis, we examine whether the reduced investments in hub companies by in-hub VCs can explain the observed increase in distance. Table A4 shows the changes in the post-Covid distance between VCs and their portfolio companies depending on whether the VC and the company are located in a hub. The results in columns (1) and (4) suggest that, on average, the distance between in-hub investors and their portfolio companies increased more than between out-of-hub VCs and their portfolio companies. Columns (2) and (5) additionally control whether the portfolio company is located in a hub. Unsurprisingly, *Hub Company* coefficient suggests that the distance to in-hub portfolio companies for in-hub investors is substantially smaller, while it is the larger for out-of-hub VCs. Finally, columns (3) and (6) reveal whether the largest increase in distance post-Covid comes from in-hub or out-of-hub investments for both types of VCs. As far as in-hub VCs are concerned, we observe that the increased distance to their portfolio companies is primarily explained by the growth of distance to companies located in hubs (column (3)). This can be driven either by VCs investing in their own hub but farther away from their headquarters compared to pre-Covid investments or by VCs investing in another hub usually located far away

(e.g., San Francisco VC investing in Boston or New York). Regarding out-of-hub VCs, the growth of distance primarily comes from investments performed in companies located outside the hubs (column (6)). Figure 2 illustrates this finding using a map of investments performed by VCs located in California. We can observe a growth of investments in regions surrounding the entrepreneurship hubs plus the appearance of some new areas far away from the usual hubs. However, we do not observe a large number of new investments in new areas.

1.6 Alternative explanations

While the expansion of web conferencing services due to the Covid-19 outbreak seems to be an intuitive contributor to the rise of distant investments, alternative explanations require some attention. This section examines whether the increase in distant investments is due to the emergence of new opportunities in areas far from VCs. Indeed, a state far away from the average VC may become attractive to investors for at least two reasons. First, the industry composition of a state may explain its attractiveness: VCs might be more inclined to invest in states that experience higher growth due to Covid-19 because they house many industries benefiting from the pandemic. If true, the increase in distance after Covid-19 will be fully explained by a faster state growth of more distant states. Second, a distant state may be appealing to investors if the fraction of new businesses located there is higher than before. If new businesses are created in states that are far away from the usual clusters, the new geographical distribution of potential investment opportunities may explain the increase in distant investments independently from the Covid-19 context.

1.6.1 Industry Change

Since the Covid-19 crisis impacted the overall economy, to conclude that VCs invest farther away due to the leveling up of the quality and the cost of information acquisition for proximate and distant companies, we first need to exclude that VCs are not investing in distant states due to a change in their industry composition. If distant areas are more developed around industries that benefited from the pandemic, VCs might have preferred to invest there even without limitations on the acquisition of soft information. Thus, some states might be experiencing higher VC financing post-Covid since they are more specialized in industries that benefited from the pandemic. To

control for this alternative explanation, we proceed in three steps.

First, in our regressions, we control for the change in the portfolio company's state growth rate due to Covid-19. We estimate the change in the state growth rate due to Covid-19 as the difference between its growth rate in 2020 and in pre-pandemic 2019. This enables us to determine the states that outperformed during the most severe Covid year. The state's growth rate is computed as the weighted average of growth rates in 3-digit NAICS industries. We use employment shares of industries in the state from Census' Business Patterns data as weights. Industry growth rates are estimated using Compustat data on listed firms' average market capitalization growth during 2019 and 2020.

Second, we directly control for the change in the portfolio company's industry growth. If those industries that benefited most from Covid are located farther away, then again the increase in distance will reflect the growth of pandemic-driven economic opportunities in more distant locations. We estimate the change in 3-digit NAICS industries using Compustat data as before. If this alternative explanation is at play, i.e. post-Covid state or industry growth explains the increase in distance between VCs and their portfolio companies, the interaction between *Post Covid* and Δ *State Growth* and/or *Post Covid* and Δ *Industry Growth* should be positive and significant while making the coefficient of *Post Covid* alone insignificant.

Finally, to ensure that our choice of industry growth measures does not drive the results in previous tests, we incorporate the findings from the Small Business Pulse Survey (SBPS). Based on the questionnaire results, we identify industries that were hurt most by Covid-19 and industries that suffered less. We then divide investments in our sample with respect to this classification. Specifically, the Small Business Pulse Survey enables us to estimate the percentage of companies in the industry that reported that Covid-19 hit their revenues in 2020 and 2021. We assign this measure to the companies in our sample based on their 3-digit NAICS industry and split it by the median percentage of firms that suffered revenue losses. If we see the increase of distance in both sets of industries, then the growth of distance is less likely to occur just because VCs are selecting companies from winning more distant industries.

Table 5 shows whether state and industry growth explain the observed increase in distance. Columns (1) and (2) focus on the relationship between distance and the change in the portfolio company's state growth. Those states that had a larger change in their growth rates due to Covid (higher Δ *State Growth*) do not seem to explain the growth of distance to investments, since the

coefficient is negative and insignificant in column (1). Similarly, column (2) reports a negative and insignificant coefficient for the interaction term *Post Covid* x Δ *State Growth*, suggesting that the acceleration or a slowdown in the states' growth does not fully explain the growth in distance post-Covid: the coefficient of *Post Covid* slightly decreases but it is still significant at 10%.

Companies from industries that suffered less from Covid (higher Δ *Industry Growth*) on average are located closer to VCs: the coefficient is negative and significant in column (3). The interaction coefficient *Post Covid* x Δ *Industry Growth*, however, is not statistically significant. Here again, the coefficient of *Post Covid* slightly decreases but remains significant at 5%. Thus, we conclude that the distance increase is not mainly explained by the growth in industries located farther from an average VC. Lastly, columns (5) and (6) show that there is no relationship between distance and the dummy for whether the portfolio company belongs to an industry that suffered more from the pandemic, according to the SBPS. *Industry Hit* variable, which is a dummy equal to 1 if the company's industry has above-median percentage of firms that lost their revenues due to Covid, is insignificant both individually and when interacted with *Post Covid*. The results are qualitatively the same if we use a top decile rather than the median for the split, or when we estimate the share of suffering companies based on the number of companies that reported decreasing employment.

1.6.2 Business Creation

To understand if the growth of distant investments observed after the Covid-19 onset is due to changes in the location of new businesses, we focus on the evolution of business applications at the state level. The Business Formation Statistics (hereafter BFS) data reports the number of business applications per state for each month. This enables us to compute the average annual growth rate of business applications as a moving average based on 12 months preceding the focal month. Since High Propensity Business Applications (HBA) are better suited to measure potential employer businesses, we construct our variables based on seasonally adjusted HBA. In our main specification, we use growth rates lagged by one month and by a quarter to account for the delay between the investment decision and the actual investment. To capture any broader effect from a pre-trend, we also identify *HighHBAGrowth* states based on business applications from 2015 to 2017. A state is defined as *HighHBAGrowth* if the state's average growth rate over these 3 years is above the average growth at the U.S. level. If such states correspond to states that are farther

away from VCs, the increase observed in distant investments may be explained by the growth in new distant businesses, independently from the Covid-19 context. In this case, interacting *HighBAGrowth* with our *Post Covid* dummy should reveal a positive and significant coefficient that captures all the significance of the *Post Covid* variable alone.

Table 6 shows that the growth in business applications is not driving our results. Columns (1) and (3) suggest that the states that experienced an important growth in high propensity business applications are located far from VCs as the coefficient is positive and significant. However, we do not observe any statistically significant coefficient when interacting the growth rate with *Post Covid*, except for the *Post Covid* variable. The last set of regressions reported in columns (5) and (6) does not contribute to challenging our main findings either. Companies located in states classified as *HighBAGrowth* are not more distant companies in which VCs invest after the Covid-19 crisis.

1.6.3 Venture Capital Activity

The last couple of years were also characterized by a boom in venture investing¹³. This was initially driven by the low interest rate environment that characterized the stock market over the past decade, thus pushing investors to seek higher yields in private markets. To this, the pandemic contributed by forcing governments to increase market liquidity. Therefore, an alternative explanation to our findings might be that the increase in distance is related not to a change in the information collection process but to a higher local competition among VCs that makes them seek investments in more distant areas. To ensure that the change in distance to investments and in other deal characteristics is not driven by too much money chasing limited local investment opportunities, we use VC fund inflows to the state of the analyzed VC lagged by one year as control. Table A1 shows the long-term relationship between total VC funds' inflows to the state and the average distance to portfolio companies for VCs in this state (the sample period is 1995-2019 using Refinitiv data and 1995-2017 using VentureSource data). The correlation between the average distance to portfolio companies and the one-year lagged venture capital amount raised by funds in the state is positive. The coefficient is small in magnitude: a 1% increase in the state's VC funds' inflows is associated with 0.03% larger distance between this state's VCs and

¹³See for example, data from the National Venture Capital Association 2022 Yearbook: <https://nvca.org/wp-content/uploads/2022/03/NVCA-2022-Yearbook-Final.pdf>

their portfolio companies. Nevertheless, in all regressions where the intensity of the VC activity can impact the outcome (i.e., in all distance regressions, board control and valuations, syndication and performance), we control for this measure of local venture capital available for investment to ensure that the relationship with *Post Covid* is not related to the increase in VC funds' inflows observed during that period.

1.7 Investment characteristics and syndication

1.7.1 Startup Characteristics

In the previous section, we documented an increase in distance between VCs and their portfolio companies following the unexpected arrival of the Covid pandemic and resulting restrictions on in-person interactions. In the literature, it is established that soft information is critically important for investing in startups because of the high information asymmetry between VCs and entrepreneurs (e.g., Tian, 2011). It is also shown that, as the distance between VCs and their portfolio companies increases, VCs try to compensate for the lower possibility of face-to-face meetings and on-site monitoring by investing in more mature companies that can have a longer track record (Sorenson and Stuart, 2001), while at the same time they reduce board membership since the oversight of distant firms is more costly (Lerner, 1995). If videoconferencing provides VCs with an adequate replacement for face-to-face meetings and monitoring, we can expect them to overcome frictions traditionally associated with distance and invest in younger firms and/or appoint more board members. In other words, they would start treating distant firms like proximate ones. On the other hand, if online meetings are an imperfect substitute for in-person interactions, VCs would be expected to behave as they used to do with more distant firms. We then investigate if VCs try to compensate for the overall change in the available soft information by choosing less risky investment behaviors. We study if they invest more often in their focus industry, in companies that have pre-VC financing, and if they set lower pre-money valuations. Finally, we test if they invest more in syndicates with other VCs.

The first aspect of VC deals we analyze is the likelihood of investing in the VC's focus industry. VC investors tend to specialize in a specific industry since it enables them to accumulate industry expertise and to build a strong network with founders and other professionals working in the sector. This helps them to collect valuable information about investment opportunities (Sorenson

and Stuart, 2001). Therefore, investments made outside of the VC's focus industry may suggest risk-taking behavior or chasing hot opportunities (Sorenson and Stuart, 2008). We construct our industry focus variable based on the 10 sectors classification from Refinitiv. We define the VC's focus industry as a broad industry in which VC invested the largest amount by the year of the analyzed investment. Table 7 shows that in the cross-section of deals in our sample, VCs are as likely to invest in companies from their focus industries after Covid as before Covid (columns (1) and (2)). However, regression results with VC firm fixed effects suggest that, within VC firms, there seems to be a preference for the deviation from the VC's focus industry after the Covid onset (columns (3) and (4)). Taken at face value, we could conclude that VCs start engaging in riskier behavior. However, the results in column (5) suggest that this might not be true. This column shows the results of the regression in which the dependent variable is a dummy equal to one if at least one VC in the syndicate specializes in the portfolio company's industry. These results show that, on average, a portfolio company might be more likely to have a VC focused on its industry after Covid, even though the coefficient is significant at the 10% level. Therefore, VCs that themselves have no expertise in the company's industry (as shown by columns (3) and (4)) are more likely to join the syndicate with the company's industry expert.

The following results reported in this section are based on our Pitchbook sample offering more details on some deal characteristics than Refinitiv. This sample consists of the first investment rounds categorized as "seed", "early round", or "accelerator" and completed between November, 2018 and June, 2021.

Table 8 reports the results of different variations of the regression equation 1.2 where the dependent variable is the age of portfolio companies. Columns (1) and (2) show that post-Covid, in a cross-section, VCs invest in more mature companies. Column (3) shows that this result holds even after adding VC firm fixed effects. Thus, within a given VC's portfolio, post-Covid, selected companies are older. This finding suggests that VCs might try to balance the limited access to soft information by selecting companies for which they can acquire other information. Consistently, when turning to the relationship between company age and distance, we observe in column (4) that more distant companies on average, are older. This observation is aligned with the argument in Sorenson and Stuart (2001) that distant VCs are more likely to invest in more mature companies to compensate for less frequent in-person interactions. What is particularly interesting from these results is that online interactions do not seem to lower frictions related to distant investments.

Before Covid, distant targets were older than proximate ones. After Covid, on average, VCs invest in more mature companies, even when they are located nearby.

We next explore whether VCs are more inclined to invest in startups that already received earlier financing from accelerators, angels, crowdfunding platforms, etc. We define a financing round categorized as “Accelerator/Incubator”, “Equity Crowdfunding”, “Product Crowdfunding”, “Grant”, or “Angel (individual)” and completed before the first VC financing as a pre-VC financing round (for these regressions we exclude rounds classified as “Accelerator/Incubator” from the sample). Table 9 shows the results of an OLS regression where the dependent variable is a dummy for having pre-VC financing. To ensure that the observed changes in company age do not drive our findings, we add company age fixed effects to our initial set of fixed effects. Overall, this table suggests that post-Covid, startups receiving VC financing are less likely to have a pre-VC financing round. Considering their inability to benefit from in-person interactions as before, we would have expected VCs to rely more on pre-VC financing to reduce their risk. However, our finding shows the opposite. At the same time, we do not find a significant effect when examining the relationship between distance and the likelihood of having pre-VC financing. Perhaps, VCs might not consider pre-VC financing as an important selection criterion that may help them to learn more about companies.

The last startup-level characteristic we explore is pre-money valuation. Investigating changes in pre-money valuations might help us better understand how the entrepreneurs’ bargaining power changed after the Covid-19 onset. Table 10 reports the results of running regression equation 1.2 where the dependent variable is the natural logarithm of the startup’s pre-money valuation. Given that during Covid-19 large amount of capital flowed to the private equity industry¹⁴ and higher supply of capital may increase startups’ valuations, as before we control for the total capital raised by the VC funds in the investor’s state lagged by one year. As more mature companies might be more likely to have higher valuations, we also keep using company age fixed effects in this table. In columns (1) and (2), cross-section level results reveal a decrease in pre-money valuations after Covid-19. However, when adding VC firm fixed effects in columns (3) and (4), we observe no significant change in valuation, whether the company is distant to the investor or not.

¹⁴See for example, the National Venture Capital Association 2022 Yearbook: <https://nvca.org/wp-content/uploads/2022/03/NVCA-2022-Yearbook-Final.pdf>

1.7.2 Board Control

Prior studies have established that venture capitalists are less likely to have a board seat in portfolio companies that are farther away from them (Lerner, 1995, Amornsiripanitch et al., 2019). One explanation is that oversight of farther away companies is more costly for venture capitalists, given that their time is scarce and valuable. Due to the widespread use of videoconferencing post-Covid, this cost may decrease, and, as a consequence, venture capitalists may be more inclined to take a board seat in startups, whether proximate or located farther away. In this section, we investigate how the number of board seats received by VCs changes post-Covid.

Table 11 presents the results of running regression equation 1.2 where the dependent variable is the number of board seats received by VCs in their portfolio companies after investing in the companies¹⁵. The sample includes first investment rounds categorized as “seed”, “early round”, or “accelerator” and completed between November, 2018 and June, 2021 in the Pitchbook dataset.

The results show a negative and significant coefficient on the *Post Covid* dummy in all specifications, suggesting that the number of board of directors appointments performed by VCs decreases post Covid-19. Column (4) also shows that there is no significant link between the number of board seat appointments and the distance between the company and the VC investor. At first, results on board seats might not seem surprising. So far, we established an overall increase in distance to investments post-pandemic, and we said that existing literature documents that the number of board seats is decreasing in distance. At the same time, if the new norms adopted post pandemic (i.e., pre- and post-investment interactions are online) are an effective new normal, we can expect VCs to demand on average more board seats, as they would normally do with companies located close to them. Results show the opposite, suggesting that online interactions might be considered not ideal for fulfilling board responsibilities and conducting post-investment activities such as the monitoring of portfolio companies, whether they are distant or not.

1.7.3 Syndicate formation

As stated by Sorenson and Stuart (2001), the geographical concentration of VCs is closely related to their pre- and post-investment activities: for VCs, identifying and evaluating oppor-

¹⁵Board of directors appointments for which Pitchbook does not have a start date of the appointment are dropped from the sample. The results hold if all of the board of directors appointments are kept assuming that all appointments took place after VCs invest in their portfolio companies, or if the board of directors appointments without start date for companies with more than one round of financing are dropped.

tunities is more straightforward when searching locally, as they invest in early-stage companies for which little information is available. In addition, monitoring and adding value through other activities is also easier when the portfolio company is not far away (Bernstein et al., 2016). This is why investing in distant companies is more challenging, and networks/syndicates are key when investing farther away. Multiple and dispersed relationships help not only to learn about potential investment opportunities but also to find co-investors who are closer to distant targets (Sorenson and Stuart, 2001). With the pandemic restrictions, communication channels changed, and proximity became no more different than distance. As online interactions became the norm for everyone, finding investments or co-investors and learning about them became online activities. Therefore, in this section, we explore whether VCs changed the way they syndicate after Covid-19.

It is an established fact in the literature that VCs co-invest more under high uncertainty or when information asymmetry is more severe (Bygrave, 1987). Indeed, syndication not only helps to share risk but also enables VCs to bring together more expertise and share information on investment opportunities (Bygrave, 1987, Lerner, 1994, Antweiler et al., 2002). Hence, as distance to investments increased after Covid, we might first expect to observe an increase in syndicated deals post-pandemic. On the contrary, as online meetings should decrease the information gap between distant and proximate companies, we might not observe a consequent increase in syndication, provided online meetings are a good alternative to in-person interactions to acquire the necessary information.

Table 12 supports the first prediction and reveals that the probability to invest with other VCs increases by around 7 percentage points (13%) post-Covid. This suggests that VCs try to compensate for changes in the information environment by reaching to their networks to get more information.

While columns (1) to (3) report specifications adding industry, state, and VC investor fixed effects progressively, column (4) presents distance-related results. This last column suggests that the VC's distance to the portfolio company does not contribute much to explaining the syndication decision.

VC networks tend to cluster geographically since investment and monitoring coordination might be more challenging when VCs are distant from one another (Sorenson and Stuart, 2001). However, with the onset of Covid, we can expect an extension of distance among syndicate partners. This process can be driven by two forces. First, VCs can reach to remote connections in their network

to obtain information about investment opportunities in the remote partner's location or simply because the cost of communication with a distant VC became smaller relative to the cost of communication with a proximate VC. Second, more distant syndicates might result from the focal VC's more distant target company inviting other VCs to join the syndicate. Even if these VCs are close to the company, they will still be far from the focal VC. We explore whether the geographical distance between syndicate members increased with the pandemic's start in a regression framework.

Table 13 shows that distance among syndicate members increased significantly post-Covid. The dependent variable in the regressions is defined as a natural logarithm of the average distance among the syndicate members calculated as an average of distances between all possible pairs of VCs in the syndicate. Columns (1) to (3) add industry, state, and VC investor fixed effects one by one. In these specifications, the coefficient of *Post Covid* varies between 0.20 and 0.28 suggesting that the average distance between syndicate members increases by 22% to 32% after the Covid onset. We then examine whether the distance between syndicate members varies with their distance to the portfolio company. Indeed, this increase in syndicate members' distance may be driven by the decision of the focal VC to make a distant investment. Column (4) shows that, when the focal VC invests in a more remote company, the distance to its syndicate members in fact is larger. But the coefficient of *Post Covid* is still positive and statistically significant, even though somewhat smaller. Thus, the distance to the portfolio company does not fully explain syndicate members' remoteness. Table A5 reports similar results when we split the sample of investments based on the location of VCs (large entrepreneurial hub or not).

Syndicate partners become more geographically distant after the Covid onset, but do syndicates include more old syndicate partners? We define old syndicate partners as those VCs that co-invested together during five years preceding the year of the analyzed investment. We calculate the proportion of old syndicate partners in the deal as a sum of all old syndicate partner pairs divided by the total number of VC pairs in this syndicate (based on all possible pairs of VCs participating in the syndicate). We are also interested to know how the propensity to partner with old syndicate members varies with the VCs' distance to the portfolio company.

Columns (1) and (2) from table 14 show that, in a cross-section of all deals, controlling for company industry or company industry and state fixed effects, VCs participate in syndicates with fewer old partners. Overall, this result is consistent with VC syndicates becoming more dispersed in space, since more distant VC firms are less likely to come from the same network (Sorenson and

Stuart, 2001). However, adding VC firm fixed effects changes the sign of the coefficient and reduces its statistical significance. Columns (3) and (4) show that, within the VC firm, the proportion of old partners in a syndicate is as high or even higher after Covid. This suggests that the initially observed change does not happen for VCs that invest before and after Covid, but the negative sign was driven by VCs that entered (or left) the market post-pandemic. Column (4) shows that this proportion slightly decreases with the distance to the portfolio company - the coefficient of $\ln(\text{Distance}+1)$ is negative and significant. This might occur when a distant company invites its local VCs to the syndicate, which are less likely to come from the focal VC's local tighter network. Table A6 additionally shows that VCs located outside large entrepreneurship hubs are those that are more likely to syndicate deals with prior syndicate partners after Covid. The coefficient of *Post Covid* is positive and strongly significant in the specifications with VC fixed effects for the subsample of such VCs.

Lastly, we aim to clarify whether, for a specific VC, the likelihood to syndicate with partners located in the proximity of the portfolio company changes after Covid. Indeed, we might expect an increased propensity to make distant investments when there are VCs around the targeted company that can supervise it after the restrictions on in-person interactions are lifted. We rely on two analyses to achieve our goal. We first look at distances between the startup and its most proximate VC investor as well as its most remote investor. We then complement our findings by investigating the likelihood of having at least one VC partner within 50 km distance from the startups. Table 15 reports the results of the first analysis and table A7 of the second one. Columns (1) to (3) of table 15 show that the minimum distance between a startup and its VCs increases post-Covid. The magnitude of the coefficients varies between 14 and 18% when including company state fixed effects while it is around 30% when no company state fixed effects are included. This finding suggests that, post-Covid, even the closest investors are more distant. Unsurprisingly, columns (4) to (6) in Table 15 confirm our baseline result about distant investments. They reveal that the distance between a startup and its most remote investor increases by more than 25% after the pandemic onset.

Table A7 additionally supports these results by showing that post-Covid, VCs invest with fewer other VCs located close to the startup, while we would have expected more partnerships with VCs nearby distant portfolio companies to alleviate information asymmetry. Interestingly, the likelihood of having at least one VC within up to an hour drive (i.e., 50 km) from the portfolio company is

lower in a cross-section of deals but is similar before and after Covid within the VC portfolio, since the coefficient is negative and statistically significant in column (1) and statistically insignificant in columns (2) and (3) where we additionally include VC fixed effects. Therefore, while the overall syndicate becomes more distant and there are fewer VCs in the proximity of the portfolio company, VCs are as likely to ensure that there is at least one investor located within a short drive distance from the company.

Overall, the results in this section suggest that VCs reach to a wider network, but are more likely to partner with their old connections and reach to at least one VC located in the targeted company's local area. These results reflect the need to gather more information (higher likelihood of syndication and more distant co-investors) and also the need to mitigate higher information uncertainty by reaching to a trusted network (higher proportion of old partners) and the network from the company's location (no lower likelihood to have at least one nearby VC in the syndicate). These results are potentially as powerful as the first set of results on distance to investments in terms of implications for the geography of entrepreneurship, as new collaboration among VCs can change the traditional information diffusion.

1.8 Preliminary insights on performance

This last section provides some early insights from the investment performance side. Although we do not have long enough time post-Covid to properly assess the consequences of pandemic-related changes on the VC industry's performance, the question of whether online deal sourcing can be better or worse than the traditional one is important enough to have a preliminary analysis. As we only have 28 months of data since the beginning of the pandemic, which is a time period lower than the average time period for exits, we first focus on the probability of raising a second round as the most reliable intermediate outcome measure¹⁶, but still, take a look at the likelihood of exiting via IPO or M&A within different time periods. To identify whether a company received a second round or whether it successfully exited, we extended our Refinitiv data until July 2022. This enables us to construct our second round variable and lose fewer observations. Thus, we analyze the probability to get a second round within 6, 12 and 18 months. In the reported results,

¹⁶Hochberg et al. (2007) highlights that one-third of the companies in their sample do not survive the first round of financing and are thus written off.

we keep the balanced structure of the data¹⁷. For exits, due to the time needed to go public or to be acquired, we examine the associated probabilities within 18 months.

When studying these probabilities, we use the same regression specifications as before, as in equation 1.2, where the dependent variable is a dummy for whether the company received a second round or not/exited or not. In exit regressions, on top of the usual controls and fixed effects used so far in the analysis, to ensure that specific market conditions do not drive our results, we follow Nahata (2008) and include a range of relevant controls. Specifically, we include the control for the VC fundraising in the investor's state in the year prior to the VC's first investment in the portfolio company as a measure of the VC capital inflows. Also, we include the median book-to-market ratio in the company's 3-digit NAICS industry, estimated based on public firms' data, in the year prior to the VC's first investment as a proxy for the VC investment environment. Finally, we control for the IPO and M&A market conditions by including a measure of the lagged number of IPOs/M&A in the quarter before the completed exit; while for companies that still did not exit, it is equal to the average of the lagged quarterly number of IPO/M&A transactions over the entire analyzed time period after the first VC investment.

Table 16 reports results on the probability of receiving a second VC financing round. When focusing on a restricted period of 6 months, we observe, in columns (1) to (3), that the likelihood of getting a second round is not different for companies that received their first VC financing during the post-Covid period compared to those funded before. Columns (4) to (9) suggest that, within 12 or 18 months, the probability of receiving a second round increases by respectively around 5 and 11 percentage points for companies that received their first round after Covid. However, it is worth noticing that we lose a lot of observations because of the data truncation in the latter specifications. In general, results suggest that at least in these first months since the beginning of the pandemic, VCs are following up with further rounds of financing to companies sourced online not less than to those companies they decided to finance before the pandemic. Table A8 in the Appendix, reports results when extending the pre-Covid period (starting from January 2010) and including industry-state fixed effects. The results are in line with those observed in table 16.

Columns (1) to (3) of table 17 report the results for the probability of going public or being acquired within 18 months. They show that the probability of exit for companies that received the

¹⁷When considering the probability of getting a second round within a year (18 months), we need to drop observations from the last 6 (12) months of 2021 in our main sample (plus first 6 months of added data for 2022) for which we are not able to identify whether a second round will exist within a year (18 months) or not.

first round of financing post-Covid is not statistically different from those that received it before the pandemic. Columns (4) to (6) and (7) to (9) separately report results for the likelihood to have an IPO and the probability to exit through M&A. The results reveal that exits via IPOs are not significantly more likely for companies that received VC financing post Covid: even though the coefficient is positive in the regressions, it is not statistically significant. At the same time, column (7) shows that the probability of M&A exit on average is lower, however, after including VC fixed effects the *Post Covid* coefficient is no longer significant. As reported in table A9 of the Appendix, the results are consistent when extending the pre-Covid period (starting from January 2018) and including industry-state fixed effects.

Thus, these preliminary findings do not exclude the possibility that companies financed after the Covid-19 pandemic perform similarly in terms of fast exits compared to those funded before Covid. Further explorations of a longer time period would enable us to support or reject these early results.

1.9 Conclusion

VC investors highly value in-person interactions to make investment decisions. They are used to meet startup founders and other investors through frequent events to collect information about existing and new opportunities. Being actively involved, their post-investment activities also require close monitoring of their portfolio companies. Academic literature has shown that VCs' on-site engagement contributes significantly to their portfolio companies' success (Bernstein et al., 2016, Gompers et al., 2020). Thus, in-person interactions are perceived as essential for success in the VC industry, both for the selection and treatment of investments. The arrival of the Covid-19 pandemic, followed by restrictions on in-person meetings, put this investment model to the test. By replacing face-to-face interactions with online meetings, the pandemic not only challenged VCs' post-investment activities requiring on-site presence but also changed the quality of soft information that VCs can collect about early-stage companies and the cost of information collection. This setting provides a unique opportunity to test the validity of the VC investment model: how does a change in soft information collection from in-person to online impact the behavior of these active financial intermediaries that highly rely on face-to-face communications? In this chapter, we empirically address this question.

We first establish that VCs broke their proximity culture and broadened their geographical horizons. We show that the distance between a VC firm and its portfolio company increases by around 27-43% after Covid. This increase in distance is in part explained by a lower likelihood of VCs to invest in their own state. It also reflects some redistribution of VC investments, with a relative increase in investments outside large entrepreneurial hubs (i.e., San Francisco, San Jose, Boston, or New York). Nevertheless, our results suggest that in-hub VCs remain careful when investing far away as their more distant investments are also more likely to be located in hubs. We observe the opposite behavior from out-of-hub VCs. Importantly, we rule out alternative explanations such as the increased attractiveness of some geographical areas and industries due to market conditions.

We then investigate changes in portfolio companies' characteristics in the post-Covid period. We find that VCs invest in more mature firms, but these firms are less likely to have pre-VC financing. We also observe that VCs are less likely to invest in their core industries. However, we do not observe any change in their pre-money valuations compared to the pre-Covid period. Our results additionally suggest that startups receiving VC financing post-Covid have fewer board appointees. Thus, VCs do not seem to increase control over them, following a behavior that used to be typical of their more remote investments before the pandemic. These results suggest that online interactions could not overcome frictions commonly associated with distance.

We next find that the syndication process is also affected by the Covid-induced interruption of in-person communication. Post-Covid, VCs are nearly 13% more likely to engage in syndicated deals. In addition, the average distance across syndicate members increases, as does the probability of investing with old syndicate partners. Besides, a syndicate is more likely to have at least one VC specialized in the company's industry. These results are in line with the expected VC behavior, given the need to obtain information about more geographically distant companies and the overall change in the available soft information about private companies.

Finally, we provide early insights into the performance of VC investments. We show preliminary findings on the probability of having a second round within 6, 12, and 18 months, and also take a look at the probability of companies going public or being acquired within 18 months since their first VC investment. Early findings suggest that companies financed after Covid-19 do not perform worse in terms of the probability to receive the second round and early exits. However, due to the short observation period available, these results should be interpreted with caution.

Overall, our results show that VCs change their investment behavior as a result of the inability to meet startup founders in-person and visit their offices. VCs reach to wider geography for their investments, deviating from their traditional approach of investing in companies that they can visit easily. The change in the structure and geography of the VC syndication network can be a potential explanation for this unconventional behavior. In fact, VCs expand the geography of their partners but also seem to risk less by leveraging their network: they collaborate with VCs with whom they have prior experience and include VCs that are experts in the portfolio company's industry in the syndicate. Thus, they seem to try to compensate for the lack of in-person due diligence with other mechanisms available to them. This balancing approach suggests that soft information is still crucial for VCs when in-person interactions are restricted because investors look for alternative ways to acquire it. Roelof Botha, the partner of Sequoia Capital mentioned above, says about raising VC financing online: "The risk, in my mind, especially at the earlier stages, is that you're not just raising money, you're recruiting a business partner. You're recruiting an investor who's going to be with you on a journey"¹⁸. With this approach to investing, it is not surprising that VCs try to be vigilant in the new environment.

Whether the new approach of distant investment will be negatively reflected in the performance of the VC investments is still something we need to wait to understand. However, some early performance indicators, such as the probability of raising the second round, suggest that these remote investments are not of poorer quality. If so, this would imply that the old VC investment model requiring in-person interactions between investors and startup teams might be becoming less relevant in the age of Zoom. We might also think that VCs overestimated the importance of in-person interactions. Our findings raise the question of the future of the VC industry and the value of active investments. Further investigations with extended data will enable us to shed more light on the evolution and importance of the traditional norms of the VC industry.

¹⁸From *McKinsey on startups* podcast. See <https://www.mckinsey.com/industries/technology-media-and-telecommunications/our-insights/global-vc-view-funding-startups-in-the-next-normal>.

1.10 Figures and Tables

Figure 1: Change in Distribution of Deals by Distance

The figure reports the shares of deals pre and post Covid, by different distance range (in km). The pre-Covid period is May 2018 - February 2020, the post-Covid period is March 2020 - December 2021.

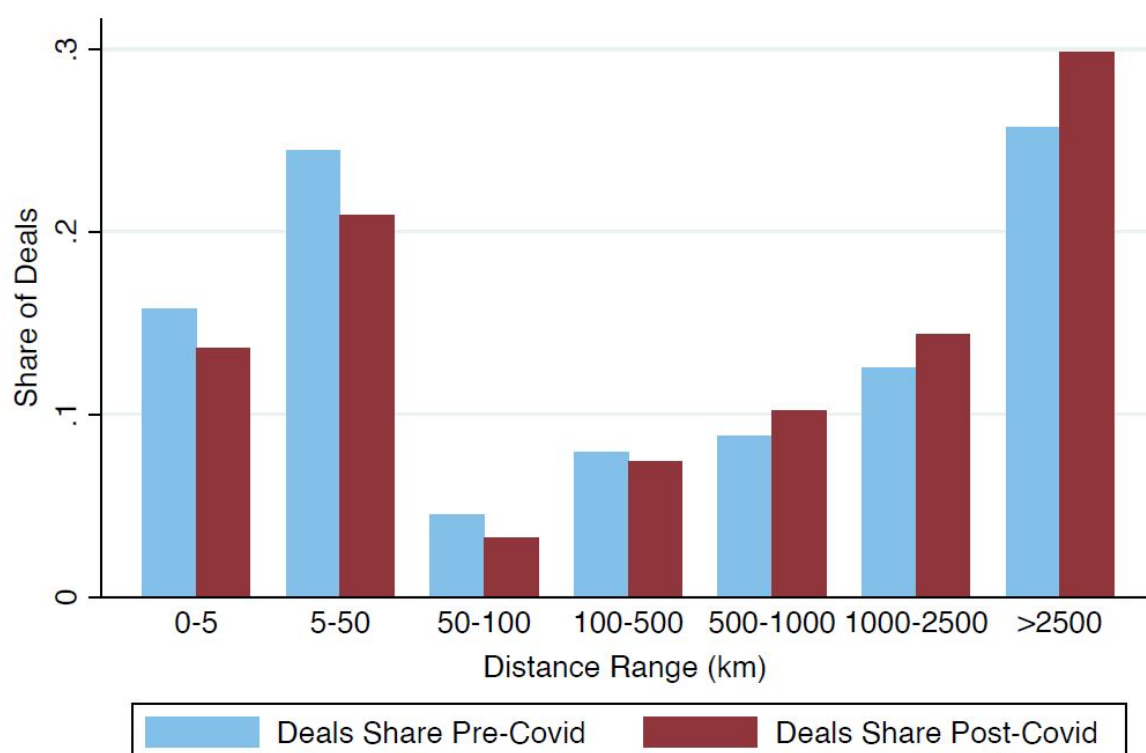


Figure 2: First Investments by Californian VCs post-Covid

The figure reports a State-County level map showing the location of portfolio companies of California-based VC investors before and after Covid. The orange color marks counties that received VC financing after Covid but not in the analyzed pre-Covid period. Blue-colored counties had already obtained VC financing pre-Covid.

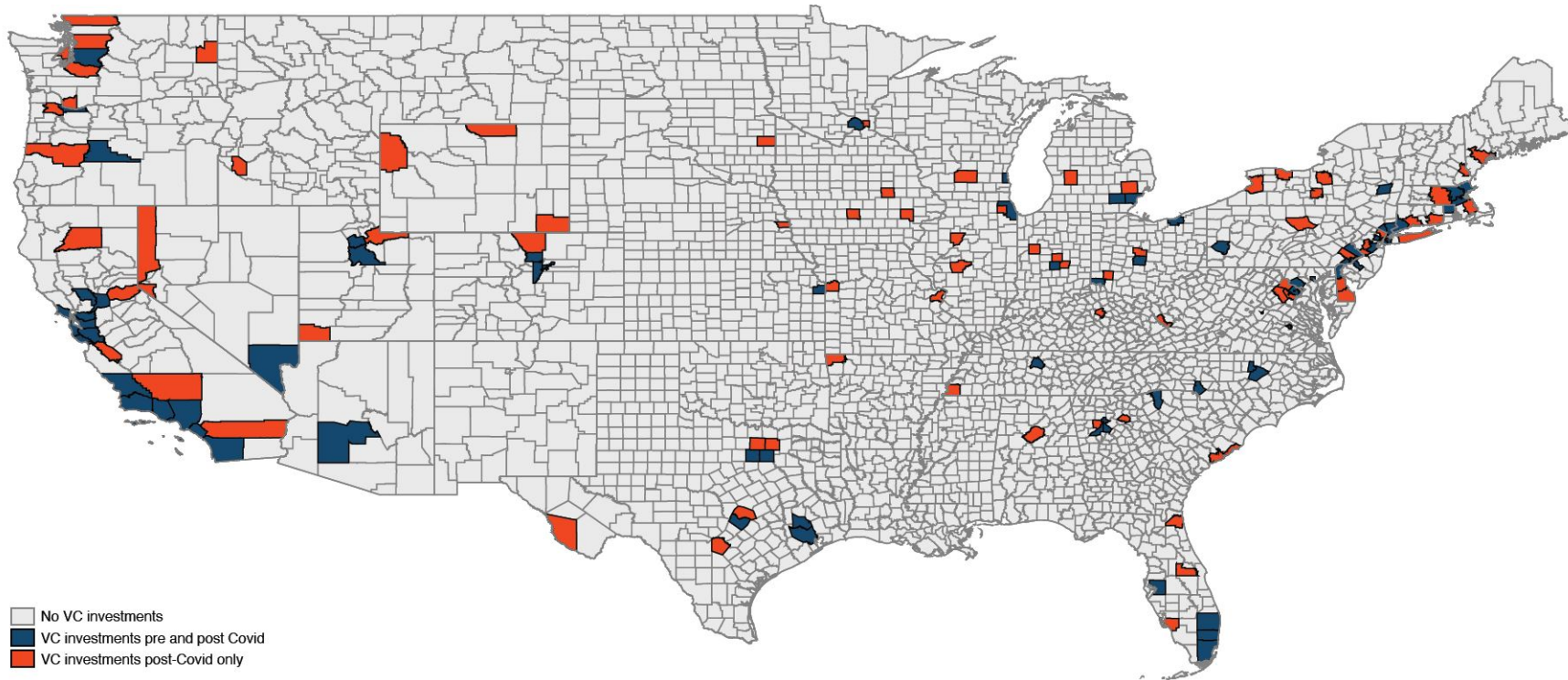


Table 1: Descriptive Statistics

The table reports the descriptive statistics for the main variables used in the analysis, with the unit of observation at the portfolio company-lead VC investor pair level. Panel A reports variables for the Refinitiv sample. The dataset includes the first investment round received by a company between May, 2018, and December, 2021 and defined as “seed” or “early round”. Panel B reports variables for the Pitchbook sample. The Pitchbook sample includes the first investment round received by a company between November, 2018, and June, 2021 and defined as “seed”, “early round”, or “accelerator”. The data for all variables includes investments in the U.S.-based companies.

	N Obs (1)	Mean (2)	Std. Dev. (3)	Min (4)	Max (5)
Panel A: Refinitiv sample					
Distance (km)	4,763	1,346	1,632	0	6,794
Ln(Distance+1)	4,763	5.29	2.69	0	8.82
P(Same State)	4,772	0.50	0.50	0	1.00
Round’s N VCs	4,772	2.29	1.60	1.00	18.00
Round Equity (\$ mil)	4,772	7.87	19.44	0.01	471
Ln(Round Equity)	4,772	1.10	1.44	-4.61	6.15
P(Seed Round)	4,772	0.15	0.35	0	1.00
CA Company	4,772	0.40	0.49	0	1.00
HUB Company	4,772	0.53	0.50	0	1.00
Panel B: Pitchbook sample					
Distance (km)	4,782	1,261	1,588	0	7,951
Ln(Distance+1)	4,782	5.18	2.71	0	8.98
P(Same State)	4,782	0.50	0.50	0	1.00
Round’s N VCs	4,782	1.88	1.32	1.00	17
Round Equity (\$ mil)	4,782	7.35	21.76	0.00	755
Ln(Round Equity)	4,782	0.67	1.84	-8.16	6.63
P(Seed Round)	4,782	0.55	0.50	0	1.00
CA Company	4,782	0.40	0.49	0	1.00
HUB Company	4,782	0.45	0.50	0	1.00
Pre-money Valuation	2,818	20.25	74.17	0.00	2,495
P(Pre-VC Financing)	4,782	0.31	0.46	0	1.00
Company Age (years)	4,679	2.29	2.12	0	28

Table 2: Post-COVID Distance to Investments (Refinitiv)

The table reports the results of an OLS regression where the dependent variable is: in columns (1) to (4), the natural logarithm of distance between the VC investor and the startup that received financing plus one; and in columns (5) and (6), a dummy variable equal to one if the portfolio company is located in the VC's state and zero otherwise. The regression dataset includes the first investment round received by a company between May, 2018, and December, 2021 and defined as "seed" or "early round". The unit of observation is the portfolio company-VC investor pair. In all specifications, controls include a natural logarithm of the round's equity investment, the number of investors participating in the round and the natural logarithm of the total capital raised by VC funds in the VC's state lagged by one year. Column (4) additionally includes a dummy variable for whether the company is located in an entrepreneurship hub. Standard errors clustered at the VC investor level. *** p<0.01, ** p<0.05, * p<0.1.

	Ln(Distance+1)				P(Same State)	
	(1)	(2)	(3)	(4)	(5)	(6)
Post Covid	0.409*** (0.063)	0.355*** (0.061)	0.261*** (0.066)	0.239*** (0.065)	-0.071*** (0.011)	-0.025** (0.011)
Observations	10,882	10,878	9,886	9,886	10,916	9,916
R-squared	0.015	0.060	0.358	0.388	0.192	0.493
Controls	✓	✓	✓	✓	✓	✓
Seed round FE	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓
State FE		✓	✓	✓	✓	✓
VC FE			✓	✓		✓

Table 3: Post-COVID Startups' Location (Refinitiv)

The table reports the results of an OLS regression where the dependent variables are: in columns (1) and (2), a dummy variable for whether the company is located in the state of California; and in columns (3) and (4), a dummy variable for whether the company is located in one of the entrepreneurial hubs (i.e., San-Francisco, Boston, New York). The regression dataset includes the first investment round received by a company between May, 2018, and December, 2021 and defined as “seed” or “early round”. The unit of observation is the portfolio company-Lead VC investor pair. In all specifications, controls include a natural logarithm of the round’s equity investment, the number of investors participating in the round and the natural logarithm of the total capital raised by VC funds in the VC’s state lagged by one year. Standard errors clustered at the VC investor level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

	CA Company		Hub Company	
	(1)	(2)	(3)	(4)
Post Covid	-0.058*** (0.015)	-0.024 (0.019)	-0.060*** (0.016)	-0.040** (0.020)
Observations	4,772	4,033	4,772	4,033
R-squared	0.123	0.384	0.129	0.380
Controls	✓	✓	✓	✓
Seed round FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
VC FE		✓		✓

Table 4: Post-Covid Startups' Location by VC Location (Refinitiv)

The table reports the results of an OLS regression where the dependent variable is a dummy variable for whether the company is located in one of the entrepreneurial hubs (i.e., San-Francisco, Boston, New York). The regression dataset includes the first investment round received by a company between May, 2018, and December, 2021 and defined as “seed” or “early round”. The unit of observation is the portfolio company-Lead VC investor pair. The sample of investments is split by whether a VC investor is located in an entrepreneurial hub (i.e., San-Francisco, New York, or Boston). In all specifications, controls include a natural logarithm of the round’s equity investment, the number of investors participating in the round, and the natural logarithm of the total capital raised by VC funds in the VC’s state lagged by one year. Standard errors clustered at the VC investor level. *** p<0.01, ** p<0.05, * p<0.1

	Hub Company			
	VC Located in a Hub		VC Located outside a Hub	
	(1)	(2)	(3)	(4)
Post Covid	-0.040*	-0.057*	0.001	0.007
	(0.021)	(0.031)	(0.023)	(0.030)
Observations	3,097	2,728	1,666	1,297
R-squared	0.016	0.211	0.059	0.406
Controls	✓	✓	✓	✓
Seed round FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
VC FE		✓		✓

**Table 5: Distance to Investments and State and Industry Growth due to Covid
(Refinitiv)**

The table reports the results of an OLS regression where the dependent variable is the natural logarithm of distance between the VC investor and the startup that received financing plus one. The regression dataset includes the first investment round received by a company between May, 2018, and December, 2021 and defined as “seed” or “early round”. The unit of observation is the portfolio company-VC investor pair. The independent variable Δ *State Growth* is a state-level measure calculated as a weighted average of changes in 3-digit NAICS industry growth rates (economy-wide) between 2019 and 2020 weighted by the industry’s employment shares in the state. Δ *Industry Growth* is an economy-wide change in 3-digit NAICS growth rates between 2019 and 2020. *Industry Hit* is a dummy variable equal to one if the company belongs to the industry that reported the above-median percentage of companies suffering from Covid. Specifically, based on the Census business survey, we estimate the percentage of companies in the industry that reported that their revenues were hit by Covid. We assign this measure to companies in our sample based on their industry and split them by the median of this industry hit measure. In all three variables, 3-digit NAICS is the NAICS industry of the portfolio company reported by Refinitiv. In all specifications, controls include a natural logarithm of the round’s equity investment, the number of investors participating in the round and the natural logarithm of the total capital raised by VC funds in the VC’s state lagged by one year. Standard errors clustered at the VC investor level. *** p<0.01, ** p<0.05, * p<0.1

	Ln(Distance+1)					
	(1)	(2)	(3)	(4)	(5)	(6)
Post Covid	0.267*** (0.068)	0.221* (0.128)	0.258*** (0.066)	0.187** (0.087)	0.258*** (0.067)	0.253*** (0.095)
Δ State Growth	-0.168 (0.414)	-0.094 (0.481)				
Post Covid x Δ State Growth		-0.119 (0.313)				
Δ Industry Growth			-0.260** (0.116)	-0.433** (0.172)		
Post Covid x Δ Industry Growth				0.283 (0.233)		
Industry Hit					0.002 (0.060)	-0.003 (0.088)
Post Covid x Industry Hit						0.009 (0.111)
Observations	9,816	9,816	9,615	9,615	9,596	9,596
R-squared	0.302	0.302	0.361	0.361	0.361	0.361
Controls	✓	✓	✓	✓	✓	✓
Stage FE	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓				
State FE			✓	✓	✓	✓
VC FE	✓	✓	✓	✓	✓	✓

Table 6: Distance to Investments and High Propensity Business Applications (HBA) growth (Refinitiv)

The table reports the results of an OLS regression where the dependent variable is the natural logarithm of distance between the VC investor and the startup that received financing plus one. *HBA Growth* corresponds to the annual growth rate in high propensity business applications at state-month level and lagged values are considered in the regressions. Columns (1) and (2) report results with monthly lags while 3-months lags are used columns (3) and (4). *HighHBAGrowth* is a dummy variable that equals one when the state has an average HBA growth rate over 2015-2017 that is above the average growth at the overall U.S. level for the same period. The regression dataset includes the first investment round received by a company between May, 2018, and December, 2021 and defined as “seed” or “early round”. The unit of observation is the portfolio company-VC investor pair. In all specifications, controls include a natural logarithm of the round’s equity investment, the number of investors participating in the round and the natural logarithm of the total capital raised by VC funds in the VC’s state lagged by one year. Standard errors clustered at the VC investor level. *** p<0.01, ** p<0.05, * p<0.1

	Ln(Distance+1)					
	(1)	(2)	(3)	(4)	(5)	(6)
Post Covid	0.228*** (0.069)	0.225*** (0.069)	0.221*** (0.071)	0.215*** (0.071)	0.262*** (0.068)	0.337** (0.152)
HBA Growth _{m-1}	0.200** (0.095)	-0.032 (0.613)				
Post Covid x HBA Growth _{m-1}		0.239 (0.627)				
HBA Growth _{m-3}			0.258** (0.109)	-0.044 (0.605)		
Post Covid x HBA Growth _{m-3}				0.310 (0.619)		
HighHBAGrowth					-0.258 (0.205)	-0.195 (0.245)
Post Covid x HighHBAGrowth						-0.101 (0.171)
Observations	9,755	9,755	9,755	9,755	9,755	9,755
R-squared	0.302	0.302	0.302	0.302	0.302	0.302
Controls	✓	✓	✓	✓	✓	✓
Seed round FE	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓
VC FE	✓	✓	✓	✓	✓	✓

Table 7: Probability of Investing in Focus Industry (Refinitiv)

The table reports the results of an OLS regression where the dependent variable is: in columns (1) to (4), a dummy variable equal to one if the portfolio company comes from the VC’s focus industry, with data at the company-VC investor pair level; in column (5), a dummy variable equal to one if the portfolio company comes from the focus industry of at least one VC participating in the round of investment, with data at the company level. The VC’s focus industry is one of ten broad industries reported by Refinitiv, in which the VC invested the largest amount by the year of the analyzed investment. In these regressions, $\ln(\text{Distance}+1)$ is the natural logarithm of distance between the VC investor and the startup that received financing plus one. The regression dataset includes the first investment round received by a company between May, 2018, and December, 2021 and defined as “seed” or “early round”. In all specifications, controls include a natural logarithm of the round’s equity investment, the number of investors participating in the round and the natural logarithm of the total capital raised by VC funds in the VC’s state lagged by one year. Standard errors are clustered at the VC investor level in columns (1) to (4) and robust standard errors are presented in column (5). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	P(Startup in VC’s Focus Industry)				
	Each VC-Startup Pair				At Least 1 VC-Startup Pair
	(1)	(2)	(3)	(4)	(5)
Post Covid	-0.002 (0.010)	-0.001 (0.010)	-0.026** (0.012)	-0.025** (0.013)	0.021* (0.012)
Ln(Distance+1)				-0.003 (0.002)	
Observations	10,919	10,916	9,916	9,886	4,768
R-squared	0.205	0.210	0.426	0.426	0.289
Controls	✓	✓	✓	✓	✓
Stage FE	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓
State FE		✓	✓	✓	✓
VC FE			✓	✓	

Table 8: Portfolio Company's Age (Pitchbook data)

The table reports the results of an OLS regression where the dependent variable is the age of the portfolio company, calculated as the difference between the year of the analyzed investment deal and the year of the company's founding plus one. In these regressions, $\ln(\text{Distance}+1)$ is the natural logarithm of distance between the VC investor and the startup that received financing plus one. The regression dataset includes the first investment round received by a company between November, 2018, and June, 2021 and defined as "seed", "early round", or "accelerator". The unit of observation is the portfolio company-Lead VC investor pair. Controls include a natural logarithm of the round's equity investment and the number of investors participating in the round in all specifications. Standard errors clustered at the VC investor level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	Portfolio Company's Age			
	(1)	(2)	(3)	(4)
Post Covid	0.179*** (0.068)	0.169** (0.067)	0.157** (0.074)	0.144* (0.074)
Ln(Distance+1)				0.054*** (0.013)
Observations	4,679	4,676	4,304	4,304
R-squared	0.015	0.055	0.261	0.264
Controls	✓	✓	✓	✓
Deal Type FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
State FE		✓	✓	✓
VC FE			✓	✓

Table 9: Pre-VC Financing (Pitchbook data)

The table reports the results of an OLS regression where the dependent variable is a dummy for having a financing round (from accelerators, angels, crowdfunding, etc.) before receiving the first VC financing. In these regressions, $\ln(\text{Distance}+1)$ is the natural logarithm of distance between the VC investor and the startup that received financing plus one. The regression dataset includes the first investment round received by a company between November, 2018, and June, 2021 and defined as “seed” or “early round”. The unit of observation is the portfolio company-Lead VC investor pair. Controls include a natural logarithm of the round’s equity investment and the number of investors participating in the round. Standard errors clustered at the VC investor level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	1(Had Pre-VC Financing)			
	(1)	(2)	(3)	(4)
Post Covid	-0.031** (0.015)	-0.034** (0.015)	-0.037** (0.017)	-0.037** (0.017)
Ln(Distance+1)				0.002 (0.004)
Observations	4,115	4,112	3,739	3,739
R-squared	0.175	0.192	0.393	0.393
Controls	✓	✓	✓	✓
Deal Type FE	✓	✓	✓	✓
Company Age FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
State FE		✓	✓	✓
VC FE			✓	✓

Table 10: Pre-money Valuations (Pitchbook data)

The table reports the results of an OLS regression where the dependent variable is the natural logarithm of the deal's pre-money valuation. In these regressions, $\ln(\text{Distance}+1)$ is the natural logarithm of distance between the VC investor and the startup that received financing plus one. The regression dataset includes the first investment round received by a company between November, 2018, and June, 2021 and defined as "seed", "early round", or "accelerator". The unit of observation is the portfolio company-Lead VC investor pair. In all specifications, controls include a natural logarithm of the round's equity investment, the number of investors participating in the round and the natural logarithm of the total capital raised by VC funds in the VC's state lagged by one year. Standard errors clustered at the VC investor level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	Ln(Pre-Money Valuation)			
	(1)	(2)	(3)	(4)
Post Covid	-0.052** (0.024)	-0.053** (0.024)	0.023 (0.030)	0.023 (0.030)
Ln(Distance+1)				0.004 (0.005)
Observations	2,760	2,759	2,382	2,382
R-squared	0.788	0.793	0.870	0.870
Controls	✓	✓	✓	✓
Deal Type FE	✓	✓	✓	✓
Company Age FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
State FE		✓	✓	✓
VC FE			✓	✓

Table 11: VCs' Appointments to the Board of Directors (Pitchbook data)

The table reports the results of an OLS regression where the dependent variable is the number of the Lead VC firm's partners appointed to the portfolio company's board of directors. In these regressions, $\ln(\text{Distance}+1)$ is the natural logarithm of distance between the VC investor and the startup that received financing plus one. The regression dataset includes the first investment round received by a company between November, 2018, and June, 2021 and defined as "seed", "early round", or "accelerator". The unit of observation is the portfolio company-Lead VC investor pair. In all specifications, controls include a natural logarithm of the round's equity investment, the number of investors participating in the round and the natural logarithm of the total capital raised by VC funds in the VC's state lagged by one year. Standard errors clustered at the VC investor level. *** p<0.01, ** p<0.05, * p<0.1.

	Number of Board of Directors Appointees			
	(1)	(2)	(3)	(4)
Post Covid	-0.039*** (0.010)	-0.041*** (0.010)	-0.050*** (0.012)	-0.050*** (0.012)
Ln(Distance+1)				-0.003 (0.002)
Observations	4,370	4,368	3,982	3,982
R-squared	0.068	0.082	0.380	0.380
Controls	✓	✓	✓	✓
Stage FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
Company Age FE	✓	✓	✓	✓
State FE		✓	✓	✓
VC FE			✓	✓

Table 12: Probability of Deal Syndication (Refinitiv)

The table reports the results of an OLS regression where the dependent variable is a dummy variable equal to one if the deal is syndicated (has more than one VC investor) and zero otherwise. In these regressions, $\ln(\text{Distance}+1)$ is the natural logarithm of distance between the VC investor and the startup that received financing. The regression dataset includes the first investment round received by a company between May, 2018, and December, 2021 and defined as “seed” or “early round”. The unit of observation is the portfolio company-Lead VC investor pair. In all specifications, controls include a natural logarithm of the round’s equity investment and the natural logarithm of the total capital raised by VC funds in the VC’s state lagged by one year. Standard errors clustered at the VC investor level. *** p<0.01, ** p<0.05, * p<0.1.

	P(Syndicated Deal)			
	(1)	(2)	(3)	(4)
Post Covid	0.034** (0.015)	0.035** (0.015)	0.070*** (0.020)	0.070*** (0.020)
Ln(Distance+1)				0.005 (0.003)
Observations	4,772	4,768	4,026	4,019
R-squared	0.110	0.118	0.383	0.382
Controls	✓	✓	✓	✓
Stage FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
State FE		✓	✓	✓
VC FE			✓	✓

Table 13: Distance Among Syndicate Members (Refinitiv)

The table reports the results of an OLS regression where the dependent variable is the natural logarithm of average distance among the syndicate members, calculated as an average of distances between all possible pairs of VCs in the syndicate, plus one. In these regressions, $\text{Ln}(\text{Distance}+1)$ is the natural logarithm of distance between the VC investor and the startup that received financing plus one. The regression dataset includes the first investment round received by a company between May, 2018, and December, 2021 and defined as “seed” or “early round”. The unit of observation is the portfolio company-VC investor pair. In all specifications, controls include a natural logarithm of the round’s equity investment, the number of investors participating in the round and the natural logarithm of the total capital raised by VC funds in the VC’s state lagged by one year. Standard errors clustered at the VC investor level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	Ln(Average Distance b/w Syndicate Members+1)			
	(1)	(2)	(3)	(4)
Post Covid	0.276*** (0.040)	0.258*** (0.041)	0.202*** (0.049)	0.130*** (0.047)
Ln(Distance+1)				0.189*** (0.010)
Observations	8,763	8,763	7,875	7,863
R-squared	0.090	0.107	0.313	0.355
Controls	✓	✓	✓	✓
Stage FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
State FE		✓	✓	✓
VC FE			✓	✓

Table 14: Average Proportion of Old Syndicate Partners (Refinitiv)

The table reports the results of an OLS regression where the dependent variable is the proportion of old syndicate partners in the round. Old syndicate partners are those VCs who co-invested together with the focal VC during five years preceding the year of the analyzed investment. The proportion of old syndicate partners in the deal is a sum of all old syndicate partner pairs divided by the total number of VC pairs in this syndicate (based on all possible pairs of VCs participating in the syndicate). In these regressions, $\ln(\text{Distance}+1)$ is the natural logarithm of distance between the VC investor and the startup that received financing. The regression dataset includes the first investment round received by a company between May, 2018, and December, 2021 and defined as “seed” or “early round”. The unit of observation is the portfolio company-VC investor pair. In all specifications, controls include a natural logarithm of the round’s equity investment, the number of investors participating in the round and the natural logarithm of the total capital raised by VC funds in the VC’s state lagged by one year. Standard errors clustered at the VC investor level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	Proportion of Old Syndicate Partners			
	(1)	(2)	(3)	(4)
Post Covid	-0.030*** (0.008)	-0.030*** (0.008)	0.014 (0.009)	0.015* (0.009)
Ln(Distance+1)				-0.005*** (0.001)
Observations	9,344	9,344	8,442	8,416
R-squared	0.084	0.096	0.444	0.445
Controls	✓	✓	✓	✓
Stage FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
State FE		✓	✓	✓
VC FE			✓	✓

Table 15: Post-Covid Minimum and Maximum Distance to Investments (Refinitiv)

The table reports the results of an OLS regression where the dependent variable is: in columns (1) to (3), the natural logarithm of distance between the startup and its most proximate VC investor; in columns (4) to (6), the natural logarithm of distance between the startup and its most remote VC investor. The regression dataset includes the first investment round received by a company between May, 2018, and December, 2021 and defined as “seed” or “early round”. The unit of observation is the portfolio company. In all specifications, controls include a natural logarithm of the round’s equity investment, the number of investors participating in the round and the natural logarithm of the total capital raised by VC funds in the VC’s state lagged by one year. Columns (3) and (6) additionally include a dummy variable for whether the company is located in an entrepreneurship hub. Robust standard errors are presented in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	Ln(Minimum Distance+1)			Ln(Maximum Distance+1)		
	(1)	(2)	(3)	(4)	(5)	(6)
Post Covid	0.264*** (0.079)	0.161** (0.064)	0.123* (0.067)	0.299*** (0.064)	0.250*** (0.066)	0.227*** (0.064)
Observations	4,767	4,763	4,763	4,767	4,763	4,763
R-squared	0.097	0.175	0.224	0.165	0.200	0.223
Controls	✓	✓	✓	✓	✓	✓
Stage FE	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓
State FE		✓	✓		✓	✓

Table 16: Probability to receive a second round of financing (Refinitiv)

The table reports the results of an OLS regression where the dependent variable is a dummy for whether the startup received a second round of financing within 6 months (columns (1) to (3)), within 12 months (columns (4) to (6)) and within 18 months (columns (7) to (9)). The regression dataset includes the first investment round received by a company between May, 2018, and December, 2021 and defined as “seed” or “early round”. The unit of observation is the portfolio company-Lead VC investor pair. Columns (4) to (6) do not include observations starting from July 2021, and columns (7) to (9) do not include observations starting from 2021 (as our extended data ends with July 2022). To keep the balanced structure of the data and to get equal periods of financing before and after Covid-19, we also removed respective number of months from the beginning of our sample for these regressions. Controls include a natural logarithm of the round’s equity investment, the number of investors participating in the round, a dummy variable for whether the company is located in a hub or not, a quarterly lagged measure for the VC market activity defined as the total VC financing, the median of the yearly book-to-market ratio of all public companies in the same NAICS3 industry. Standard errors clustered at the VC investor level. *** p<0.01, ** p<0.05, * p<0.1.

	P(Second Round)								
	Within 6 months			Within 12 months			Within 18 months		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Post Covid	0.006 (0.009)	0.014 (0.013)	0.014 (0.013)	0.050*** (0.015)	0.063*** (0.022)	0.061*** (0.022)	0.109*** (0.023)	0.091*** (0.032)	0.090*** (0.031)
Ln(Distance+1)			0.002 (0.002)			0.005 (0.004)			0.003 (0.006)
Observations	4,768	4,026	4,019	3,355	2,699	2,698	2,024	1,519	1,518
R-squared	0.019	0.201	0.201	0.028	0.229	0.230	0.054	0.304	0.304
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Seed round FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
VC FE		✓	✓		✓	✓		✓	✓

Table 17: Probability to exit through IPO or M&A (Refinitiv)

The table reports the results of an OLS regression where the dependent variable is a dummy for whether the startup went public or was acquired (columns (1) to (3)) within 18 months, and whether it exited with IPO (columns (4) to (6)) and M&A (columns (7) to (9)) separately. The regression dataset includes the first investment round received by a company between May, 2019, and December, 2020 and defined as “seed” or “early round” (while the outcomes are observed until July, 2022). The unit of observation is the portfolio company-Lead VC investor pair. Controls include a natural logarithm of the round’s equity investment, the number of investors participating in the round, a dummy variable for whether the company is located in an entrepreneurship hub or not, a quarterly lagged measure for the VC market activity defined as the total VC financing, the median of the yearly book-to-market ratio of all public companies in the same NAICS3 industry, and a lagged measure of the number of IPOs and M&As for columns (1) to (3), and of IPOs and M&A separately in columns (3) to (6) and (7) to (9), respectively. Standard errors clustered at the VC investor level. *** p<0.01, ** p<0.05, * p<0.1.

	Probability of Exit within 18 Months								
	P(IPO or M&A)			P(IPO)			P(M&A)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Post Covid	-0.024 (0.028)	-0.019 (0.031)	-0.018 (0.031)	0.026 (0.021)	0.020 (0.024)	0.020 (0.024)	-0.043** (0.022)	-0.039 (0.025)	-0.039 (0.025)
Ln(Distance+1)			0.002 (0.002)			0.001 (0.002)			0.001 (0.002)
Observations	1,983	1,485	1,484	1,983	1,485	1,484	1,959	1,461	1,460
R-squared	0.063	0.351	0.352	0.108	0.428	0.428	0.041	0.290	0.290
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Seed round FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
VC FE		✓	✓		✓	✓		✓	✓

1.11 Appendix

Figure A1: Event-Study

The plot presents coefficient estimates with 95% confidence intervals of the OLS regression in which the dependent variable is a dummy equal to one if a portfolio company is located outside the VC's state and the independent variables are dummies for 6-month periods. The unit of observation is the portfolio company - VC investor pair. The regression dataset includes the first investment round received by a company between January, 2017, and December, 2021 and defined as “seed” or “early round”. We control for the seasonality in VC investments by including month fixed effects. Standard errors clustered at the VC investor level.

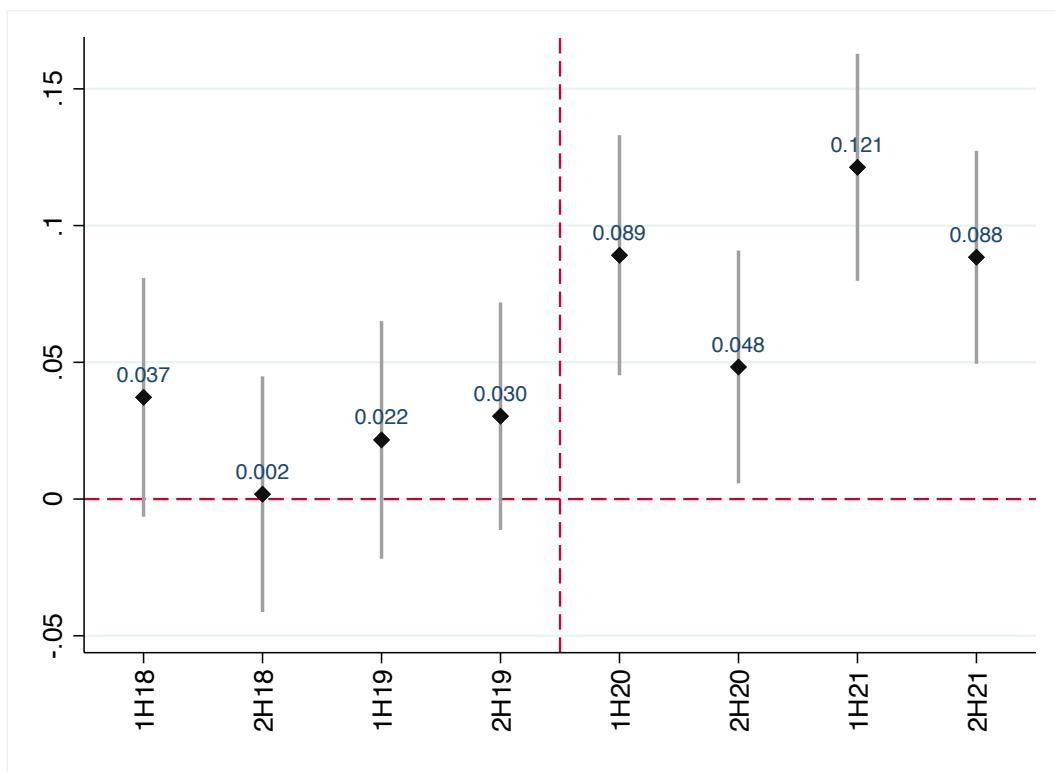


Table A1: VC Fundraising and Distance to Investments - Long-Term Analysis

The table reports the results of an OLS regression where the dependent variable is: in columns (1) to (3), the natural logarithm of the average distance between the VC investor and its portfolio company plus one, where the average is estimated across all deals satisfying the below criteria in a VC's state-year; in columns (4) to (6), an average probability that a VC's portfolio company is located outside the VC's headquarters state, where the average is calculated across all deals satisfying the below criteria in a VC's state-year. The regression dataset includes VC investment rounds received by companies between 1995 and 2019 (columns 1, 2, 4, 5) or 1995 and 2017 (columns 3 and 6) and defined as "seed" or "early round". The independent variables are: in columns (1) and (4), the natural logarithm of total VC capital raised by U.S. funds headquartered in the state each year (deflated) as reported by Refinitiv's *Amount Raised* variable; in columns (2) and (5), the natural logarithm of total size of funds headquartered in the state by vintage year (deflated) as reported by Refinitiv's *Fund Size* variable; in columns (3) and (6), the natural logarithm of total size of funds headquartered in the state by vintage year (deflated) as reported by VentureSource. Fundraising data from Refinitiv in this analysis covers the period of 1995-2019 and data from VentureSource 1995-2017. All measures of fundraising are lagged by one year. The unit of observation is U.S. state-year. All regressions include the VC state fixed effects. All regressions are weighted by the number of deals in the state-year. Standard errors clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1.

	Ln(Distance+1)			P(Same State)		
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Total Funds Raised) (Refinitiv)	0.033*** (0.012)			-0.016*** (0.003)		
Ln(Total Funds Size) (Refinitiv)		0.026* (0.015)			-0.013*** (0.004)	
Ln(Total Funds Size) (VS)			0.004 (0.012)			-0.003 (0.004)
Observations	1,017	1,023	902	1,040	1,046	902
R-squared	0.513	0.511	0.531	0.738	0.735	0.732
VC State FE	✓	✓	✓	✓	✓	✓

Table A2: Post-Covid Distance to Investments - Sample of Lead VCs' Investments (Pitchbook data)

The table reports the results of an OLS regression where the dependent variable is the natural logarithm of distance between the VC investor and the startup that received financing. The regression dataset includes the first investment round received by a company between November, 2018, and June, 2021 and defined as "seed", "early round", or "accelerator". The unit of observation is the portfolio company-Lead VC investor pair. In all specifications, controls include a natural logarithm of the round's equity investment, the number of investors participating in the round and the natural logarithm of the total capital raised by VC funds in the VC's state lagged by one year. Column (4) additionally includes a dummy variable for whether the company is located in an entrepreneurship hub. Standard errors clustered at the VC investor level. *** p<0.01, ** p<0.05, * p<0.1.

	Ln(Distance+1)			
	(1)	(2)	(3)	(4)
Post Covid	0.328*** (0.084)	0.282*** (0.083)	0.245*** (0.092)	0.209** (0.092)
Observations	4,782	4,780	4,409	4,409
R-squared	0.023	0.071	0.429	0.452
Controls	✓	✓	✓	✓
Deal Stage FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
State FE		✓	✓	✓
VC FE			✓	✓

Table A3: Post-Covid Distance to Investments - Split by VC Experience (Refinitiv)

The table reports the results of an OLS regression where the dependent variable is the natural logarithm of distance between the VC investor and the startup that received financing plus one. The regression dataset includes the first investment round received by a company between May, 2018, and December, 2021 and defined as “seed” or “early round”. The unit of observation is the portfolio company-VC investor pair. The sample is split between VCs with an above median experience and VCs with a below median experience. Experience is measured as the total number of unique companies the VC invested in by 2018 (year before the observation period starts). The results are robust to different measures of experience. In all specifications, controls include a natural logarithm of the round’s equity investment, the number of investors participating in the round and the natural logarithm of the total capital raised by VC funds in the VC’s state lagged by one year. Standard errors clustered at the VC investor level. *** p<0.01, ** p<0.05, * p<0.1.

	Ln(Distance+1)					
	Less Experienced VCs			More Experienced VCs		
	(1)	(2)	(3)	(4)	(5)	(6)
Post Covid	0.410*** (0.089)	0.368*** (0.089)	0.347*** (0.101)	0.286*** (0.099)	0.220** (0.093)	0.186* (0.101)
Observations	4,547	4,543	4,021	4,484	4,480	4,388
R-squared	0.019	0.071	0.395	0.012	0.077	0.308
Controls	✓	✓	✓	✓	✓	✓
Seed round FE	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓
State FE		✓	✓		✓	✓
VC FE			✓			✓

Table A4: Post-Covid Distance to Investments - Split by VC Location (Refinitiv)

The table reports the results of an OLS regression where the dependent variable is the natural logarithm of distance between the VC investor and the startup that received financing plus one. The regression dataset includes the first investment round received by a company between May, 2018, and December, 2021 and defined as “seed” or “early round”. The unit of observation is the portfolio company-VC investor pair. The sample of investments is split by whether a VC investor is located in an entrepreneurship hub (i.e., San-Francisco, New York, or Boston). *Hub Company* is a dummy variable equal to one if the portfolio company is located in an entrepreneurship hub and zero otherwise. In all specifications, controls include a natural logarithm of the round’s equity investment, the number of investors participating in the round and the natural logarithm of the total capital raised by VC funds in the VC’s state lagged by one year. Standard errors clustered at the VC investor level. *** p<0.01, ** p<0.05, * p<0.1.

	Ln(Distance+1)					
	VC Located in a Hub			VC Located outside a Hub		
	(1)	(2)	(3)	(4)	(5)	(6)
Post Covid	0.246** (0.100)	0.234** (0.096)	0.092 (0.095)	0.176* (0.092)	0.178** (0.088)	0.275** (0.120)
Hub Company		-2.793*** (0.114)	-2.915*** (0.132)		1.566*** (0.216)	1.741*** (0.243)
Post Covid x Hub Company			0.196* (0.110)			-0.292* (0.151)
Observations	6,691	6,691	6,691	3,180	3,180	3,180
R-squared	0.374	0.450	0.450	0.519	0.543	0.544
Controls	✓	✓	✓	✓	✓	✓
Seed round FE	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓
VC FE	✓	✓	✓	✓	✓	✓

Table A5: Distance Among Syndicate Members by VC Location (Refinitiv)

The table reports the results of an OLS regression where the dependent variable is the natural logarithm of average distance among the syndicate members, calculated as an average of distances between all possible pairs of VCs in the syndicate, plus one. In these regressions, $\ln(\text{Distance}+1)$ is the natural logarithm of one plus distance between the VC investor and the startup that received financing. The regression dataset includes the first investment round received by a company between May, 2018, and December, 2021 and defined as “seed” or “early round”. The unit of observation is the portfolio company-VC investor pair. The sample of investments is split by whether a VC investor is located in an entrepreneurship hub (i.e., San-Francisco, New York, or Boston). In all specifications, controls include a natural logarithm of the round’s equity investment, the number of investors participating in the round and the natural logarithm of the total capital raised by VC funds in the VC’s state lagged by one year. Standard errors clustered at the VC investor level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	Ln(Average Distance b/w Syndicate Members+1)					
	VC Located in a Hub			VC Located outside a Hub		
	(1)	(2)	(3)	(4)	(5)	(6)
Post Covid	0.312*** (0.055)	0.270*** (0.078)	0.206*** (0.075)	0.240*** (0.056)	0.147** (0.068)	0.085 (0.062)
Ln(Distance+1)			0.180*** (0.012)			0.209*** (0.018)
Observations	5,962	5,512	5,503	2,787	2,352	2,349
R-squared	0.136	0.304	0.337	0.128	0.339	0.403
Controls	✓	✓	✓	✓	✓	✓
Seed round FE	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓
VC FE		✓	✓		✓	✓

Table A6: Average Proportion of Old Syndicate Members by VC Location (Refinitiv)

The table reports the results of an OLS regression where the dependent variable is the proportion of old syndicate partners in the round. Old syndicate partners are those VCs who co-invested together with the focal VC during five years preceding the year of the analyzed investment. The proportion of old syndicate partners in the deal is a sum of all old syndicate partner pairs divided by the total number of VC pairs in this syndicate (based on all possible pairs of VCs participating in the syndicate). In these regressions, $\ln(\text{Distance}+1)$ is the natural logarithm of one plus distance between the VC investor and the startup that received financing. The regression dataset includes the first investment round received by a company between May, 2018, and December, 2021 and defined as “seed” or “early round”. The unit of observation is the portfolio company-VC investor pair. The sample of investments is split by whether a VC investor is located in a large entrepreneurial hub (i.e., San-Francisco, New York, or Boston). In all specifications, controls include a natural logarithm of the round’s equity investment, the number of investors participating in the round and the natural logarithm of the total capital raised by VC funds in the VC’s state lagged by one year. Standard errors clustered at the VC investor level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	Proportion of Old Syndicate Partners					
	VC Located in a Hub			VC Located outside a Hub		
	(1)	(2)	(3)	(4)	(5)	(6)
Post Covid	-0.051*** (0.011)	-0.020 (0.013)	-0.019 (0.013)	0.006 (0.013)	0.055*** (0.015)	0.057*** (0.015)
Ln(Distance+1)			-0.004*** (0.002)			-0.006** (0.003)
Observations	6,339	5,888	5,879	2,978	2,533	2,526
R-squared	0.111	0.449	0.449	0.081	0.434	0.435
Controls	✓	✓	✓	✓	✓	✓
Seed round FE	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓
VC FE		✓	✓		✓	✓

Table A7: Presence of Local Syndicate Partners (Refinitiv)

The table reports the results of an OLS regression where the dependent variables are: in columns (1) to (3), a dummy variable for whether there is at least one VC within 50 km distance from the startup (excluding the analyzed VC); in columns (4) to (6), the number of other VCs located in within 50km distance from the startup (excluding the analyzed VC). Thus, the regression tries to answer the question "for a specific VC, what is the likelihood that she will have syndicate partners located in the proximity to the portfolio company?". In these regressions, $\ln(\text{Distance}+1)$ is the natural logarithm of distance between the analyzed VC investor and the startup that received financing plus one. The regression dataset includes the first investment round received by a company between May, 2018, and December, 2021 and defined as "seed" or "early round". The unit of observation is the portfolio company-VC investor pair. In all specifications, controls include a natural logarithm of the round's equity investment, the number of investors participating in the round and the natural logarithm of the total capital raised by VC funds in the VC's state lagged by one year. Standard errors clustered at the VC investor level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	P(Local VC in 50km)			N Local VCs in 50km		
	(1)	(2)	(3)	(4)	(5)	(6)
Post Covid	-0.027*** (0.009)	-0.007 (0.011)	0.004 (0.011)	-0.179*** (0.020)	-0.158*** (0.025)	-0.131*** (0.024)
Ln(Distance+1)			-0.039*** (0.003)			-0.100*** (0.007)
Observations	10,919	9,920	9,892	10,919	9,920	9,892
R-squared	0.197	0.322	0.358	0.372	0.467	0.506
Controls	✓	✓	✓	✓	✓	✓
Stage FE	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓
VC FE		✓	✓		✓	✓

Table A8: Probability to receive a second round of financing (Refinitiv) - Extended Time Series

The table reports the results of an OLS regression where the dependent variable is a dummy for whether the startup received a second round of financing within 6 months (columns (1) to (3)), within 12 months (columns (4) to (6)) and within 18 months (columns (7) to (9)). The regression dataset includes the first investment round received by a company between January, 2010, and December, 2021 and defined as “seed” or “early round”. The unit of observation is the portfolio company-Lead VC investor pair. Columns (4) to (6) do not include observations starting from July 2021, and columns (7) to (9) do not include observations starting from 2021 (as our extended data ends with July 2022). Controls include a natural logarithm of the round’s equity investment, the number of investors participating in the round, a dummy variable for whether the company is located in a hub or not, a quarterly lagged measure for the VC market activity defined as the total VC financing, the median of the yearly book-to-market ratio of all public companies in the same NAICS3 industry. Standard errors clustered at the VC investor and year level. *** p<0.01, ** p<0.05, * p<0.1.

	P(Second Round)								
	Within 6 months			Within 12 months			Within 18 months		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Post Covid	-0.014 (0.012)	0.026*** (0.008)	0.026*** (0.008)	0.001 (0.028)	0.053*** (0.016)	0.053*** (0.016)	0.026 (0.025)	0.074*** (0.020)	0.073*** (0.020)
Ln(Distance+1)			0.001 (0.001)			0.001 (0.002)			0.003* (0.002)
Observations	12,264	11,221	11,204	11,384	10,395	10,382	10,547	9,619	9,607
R-squared	0.030	0.148	0.147	0.034	0.159	0.159	0.040	0.178	0.178
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Seed round FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Industry X State FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
VC FE		✓	✓		✓	✓		✓	✓

Table A9: Probability to exit through IPO or M&A (Refinitiv) - Extended Time Series

The table reports the results of an OLS regression where the dependent variable is a dummy for whether the startup went public or was acquired (columns (1) to (3)) within 18 months, and whether it exited with IPO (columns (4) to (6)) and M&A (columns (7) to (9)) separately. The regression dataset includes the first investment round received by a company between January, 2018, and December, 2020 and defined as “seed” or “early round” (while the outcomes are observed until July, 2022). The unit of observation is the portfolio company-Lead VC investor pair. Controls include a natural logarithm of the round’s equity investment, the number of investors participating in the round, a dummy variable for whether the company is located in an entrepreneurship hub or not, a quarterly lagged measure for the VC market activity defined as the total VC financing, the median of the yearly book-to-market ratio of all public companies in the same NAICS3 industry, and a lagged measure of the number of IPOs and M&As for columns (1) to (3), and of IPOs and M&A separately in columns (3) to (6) and (7) to (9), respectively. Standard errors clustered at the VC investor and year level. *** p<0.01, ** p<0.05, * p<0.1.

	Probability of Exit within 18 Months								
	P(IPO or M&A)			P(IPO)			P(M&A)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Post Covid	-0.009 (0.028)	0.009 (0.029)	0.009 (0.029)	0.028 (0.011)	0.026 (0.019)	0.026 (0.019)	-0.011 (0.035)	0.002 (0.036)	0.002 (0.036)
Ln(Distance+1)			0.003 (0.003)			0.002 (0.002)			0.001 (0.001)
Observations	3,269	2,622	2,619	3,269	2,622	2,619	3,230	2,583	2,580
R-squared	0.083	0.294	0.295	0.117	0.319	0.320	0.045	0.245	0.245
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Seed round FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
VC FE		✓	✓		✓	✓		✓	✓

Chapter 2

On the Stigma of Failure Under Subjective Beliefs

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Abstract

Behavioral biases and agency frictions are essential to the financing of new ventures. In this chapter, I develop a moral hazard model with subjective beliefs that captures distinct forms of behavioral biases and identifies conditions under which an entrepreneur will experience the stigma of failure. I show that while overconfidence protects entrepreneurs from the observable consequences of being stigmatized, optimism alone should not. Hence, investors are more likely to finance negative NPV projects when optimistic entrepreneurs are mistaken for overconfident. Such suboptimal decisions also appear when investors are optimistic, in which case entrepreneurial overconfidence fosters the excess financing of negative NPV projects. On the contrary, when investors are pessimistic, entrepreneurial overconfidence reduces the underfinancing of good projects. As economic conditions may influence beliefs, I also discuss macroeconomic implications and provide empirical predictions.

2.1 Introduction

Why is failure seen as a consequence of experimentation that is a stepping stone to future success in some circles while it is viewed as out of the expected social norm in others (Kerr et al., 2014, Burchell et al., 2006)? Traditionally, in the US, business failure was assigned to an individual's own misbehavior. A cultural revolution changed this view, and it is now considered to be a result of external factors rather than internal ones (Efrat, 2006). Thus, the stigma of failure became less important in the US, while it is still notable in Europe and Asia ¹. This contributes to explaining cross-country differences in entrepreneurial market activity through various channels. First, it plays an essential role in business creation through the decisions of entrepreneurs to start a venture or the decisions of investors to finance them (Landier, 2005). Second, it affects the quality of the funded projects, and the degree of innovation (Tian and Wang, 2014, Nanda and Rhodes-Kropf, 2017). That is why the stigma of failure is an important concern that still appears on the agenda of the European Commission ² and raises a large debate around the optimal public memory of negative records. In this chapter, I propose to take a behavioral approach to study the stigmatization of entrepreneurial failure. More specifically, I examine how behavioral biases affect the stigmatization of entrepreneurial failure.

The financing of new ventures is known to be mainly determined by agency frictions. At the same time, individuals' beliefs are essential for the perception of such frictions. Therefore, both the stigma of failure and behavioral biases need to be examined from this perspective. As supported by many studies, entrepreneurs are subject to overconfidence and optimism biases (Cooper et al., 1988, Busenitz and Barney, 1997, Cassar, 2010). Such biases have important consequences on career choices and economic decisions (Puri and Robinson, 2007, Astebro et al., 2014). By fostering excess entry in entrepreneurial markets (Camerer and Lovallo, 1999, Townsend et al., 2010) for instance, they may balance the negative effects of the stigma of failure. However, learning more about the benefits and drawbacks of such biases requires to consider investors' beliefs as well. Most of the behavioral studies define either the principal or the agent as irrational, but not both. I differ from them in order to introduce the notion of stigma exogenously in the moral hazard model I develop. I investigate the role played by subjective beliefs in the decision to finance entrepreneurs

¹The fear of failure rate reported by the GEM survey in 2019 is around 44% for the UK and Japan while it is established to 35% for the US.

²See their second chance policy.

who have already experienced a failure.

I consider that an entrepreneur (referred to here as ‘she’) may be indirectly stigmatized by an investor (referred to here as ‘he’) if he has a negative and wrong perception of her ability due to her past failure. As a result, she may be refused access to finance or have to pay more to get it. These are the direct and observable consequences of being stigmatized. As a negative perception of failure does not always result in an observable stigma, it is interesting to consider perceptions and decisions reflecting stigma separately. In general, studies around the stigma of failure, in finance, focus on the observed stigma of failure, perceptions being implicit. To my knowledge, this study is the first one to cross behavioral biases and the stigma of failure in a theoretical framework. In addition, building my analysis on a moral hazard problem enables me to clearly distinguish overconfidence from optimism and show that they do not play the same role in getting access to finance.

Despite the frequent mention of overconfidence and optimism in behavioral entrepreneurial research, the distinction between these two biases is not always clear. There are three common definitions of overconfidence in the literature (Moore and Healy, 2008). Overconfidence usually refers to the overestimation of one’s actual ability or performance. It could also correspond to the overplacement of one’s performance relative to others (known as the better-than-average effect). Lastly, overconfidence may be defined as the overprecision of one’s beliefs in an analysis. As far as optimism is concerned, it is more globally described as the overestimation of the likelihood of positive events and the underestimation of the likelihood of negative events (Weinstein, 1980). While overconfidence implicitly requires one to make estimations conditional on some involvement (ability, performance), optimism does not. Hence, overconfidence could be defined as a form of optimism, but the latter is not systematically related to overconfidence. For instance, an overconfident entrepreneur may think that success (a positive event) is more likely to occur than failure due to her ability. She may be characterized as optimistic as well since she overestimates the likelihood of a positive event. However, if she believes that success is more likely to occur due to her luck, then we cannot state that she is overconfident. In this case, the overestimation of the success probability is not related to her ability. Thus, there is a subtle difference between these two notions that are often employed interchangeably. In a sense, optimism covers much more than overconfidence and is more appropriate when the origin of the overestimation is unknown. In this chapter, by optimism, I refer to baseline optimism, that is, the case where there is no

overconfidence at all.

My main findings suggest that entrepreneurial overconfidence prevents the emergence of stigma while optimism alone should not. In the model I present, an investor can choose to finance either the project of a first-time entrepreneur (new entrant) or the project of an entrepreneur who has already failed. The projects are similar in all aspects, and the main difference between the two entrepreneurs is their respective histories. Thus, stigma appears if the investor prefers to finance the first-time entrepreneur rather than the failed one. I show that, when the negative perception of failure is moderate, entrepreneurial overconfidence enables one to avoid the stigma of failure. Indeed, overconfidence plays a role in reducing the agency rent since an overconfident individual is convinced by the high likelihood of success when she behaves. Namely, overconfident entrepreneurs will require less than a realistic one to behave. Therefore, investors may extract an additional rent from overconfident entrepreneurs and thus prefer to finance such entrepreneurs even though they experienced a past failure. However, this is not true for optimism since the optimal contract is the same for an optimistic and a rational entrepreneur. Considering that optimistic entrepreneurs overestimate the odds of success regardless of their own effort, incentives to behave are not affected by optimism.

In practice, it may be difficult for investors to recognize entrepreneurs who are only optimistic and those who are overconfident. Therefore, due to the confusion between these two biases, optimistic entrepreneurs may obtain financing as well, despite negative perceptions of failure. Nevertheless, as they will be proposed a contract offer intended for overconfident entrepreneurs, they will still feel stigmatized if they accept it. Indeed, when contracting with overconfident entrepreneurs, the agency rent is reduced, and investors offer them lower shares compared to rational or underconfident entrepreneurs. In a sense, it is costlier to get access to financing for overconfident entrepreneurs as they leave a higher fraction of revenue to investors. However, this cannot be interpreted as a form of stigma since this is not due to the history of the entrepreneur, it is only due to entrepreneurs' biased beliefs. Moreover, from the overconfident entrepreneur's viewpoint, there is no issue since her expected profit is high enough. For an optimistic entrepreneur, it is different. If she is mistaken for an overconfident entrepreneur, she will not have enough incentives to behave due to this low stake. As a consequence, the likelihood of failure for the project will increase. In this case, the investor provides financing to a negative NPV project by confounding optimism and overconfidence.

I also show that other situations result in the financing of negative NPV projects. More specifically, I explain that, even though investors' subjective beliefs do not influence the optimal contract, they play an essential role in their financing decisions. As long as an entrepreneur is not highly underconfident, that is, as long as an entrepreneur has access to finance, optimistic investors may finance negative NPV projects, and pessimistic ones may refuse positive NPV projects. Such decisions are socially undesirable and are the consequences of the deviation from rationality by investors. In addition, when investors are optimistic, entrepreneurial overconfidence fosters the excess financing of negative NPV projects. This result implies that when entrepreneurial overconfidence is predominant, investor rationality or even pessimism are socially more desirable to prevent the funding of bad projects. On the contrary, if investors are too pessimistic, entrepreneurial overconfidence becomes preferable as it avoids the underfinancing of good projects.

When investors do not have negative perceptions of failure, I argue that stigma appears only in a subjective form. Access to finance is refused to underconfident entrepreneurs. However, this decision is not due to their past failure, it is related to the high level of agency rent implied by underconfidence. Therefore, there is no stigmatization of failure from an objective perspective. From the failed entrepreneur's viewpoint, as long as the investor provides financing to a new entrant, she will perceive her impossibility to be financed as a stigmatization of failure. I further establish that this subjective stigma is alleviated when the investor overvalues knowledge acquisition through experience or learning from failure. In this case, he overestimates the ability of the failed entrepreneur compared to the first-time entrepreneur. Consequently, even underconfident entrepreneurs may obtain financing. Rational and overconfident entrepreneurs are not stigmatized at all in this case. In contrast, if the past experience influences the perception of the investor enough, the latter will prefer to finance failed entrepreneurs' projects. Thus, this chapter suggests that to not suffer from a stigma of failure, an entrepreneur should either be overconfident or she should ask for financing from an investor who puts enough weight on past experiences.

It contributes to both behavioral and entrepreneurial finance literature. It proposes to take a novel perspective to analyze the stigma of failure by focusing on subjective beliefs. If, at first glance, being overconfident seems to be detrimental to entrepreneurs due to the low share they receive, this chapter shows that such a bias enables them to have easier access to finance. The main empirical prediction of the chapter is that overconfident and optimistic entrepreneurs, who have already

failed, are more likely to obtain financing for subsequent ventures than others. Nevertheless, failure is more likely to occur among projects funded by optimistic investors while projects financed by pessimistic or rational investors are expected to have greater success rates. If capturing investors' degree of pessimism or optimism could be possible with aggregate sentiment measures, it is more challenging to find appropriate measures of overconfidence or optimism for entrepreneurs. With a possibility to separate these two biases empirically, the observed likelihood of failure should be stronger for optimistic entrepreneurs.

Also, economic conditions have a role to play in accessing finance. Both investors' extrapolative beliefs and expectations of future revenue, or success, facilitate the financing of entrepreneurs in good times. The stigmatization of failure is expected to be sensitive to business cycles as well. We should observe less direct stigma of failure during booms compared to busts. If the period when an entrepreneur chooses to start a new venture is important, from the stigma perspective, the timing of the closure is even more essential. Failures occurring during bad economic conditions are less likely to be attributed to internal factors. This is particularly true for the Covid-19 crisis during which some closures will be inevitable. Thus, the stigmatization of failure should be reduced after economic downturns, and those who experienced their failures during such bad times should have easier access to new financings. As observed with investors, entrepreneurs may also behave strategically, by delaying their failure, to protect their reputation and avoid stigma.

The remainder of the chapter proceeds as follows. I review the related literature in Section 2.2. I then present the theoretical framework in Section 2.3 and the benchmark case in Section 2.4. Deviation from objective beliefs and emergence of stigma are considered in Section 2.5 and Section 2.6, respectively. I additionally provide a discussion about project quality and business cycles in Section 2.7 and Section 2.8 before concluding in Section 2.9.

2.2 Related Literature

Studies related to behavioral biases in entrepreneurial finance are abundant. Most of them focus on overconfidence and optimism, two biases to which entrepreneurs are particularly subject (Busenitz and Barney, 1997, Cooper et al., 1988, De Meza and Southey, 1996, Camerer and Lovallo, 1999, Cassar, 2010, Townsend et al., 2010). Nevertheless, the distinction between these two biases is not always clear and they are often employed interchangeably. Moore and Healy (2008) define overconfidence in three different ways: as an overestimation of one's actual ability, as an overplacement of one's performance relative to others (which is also known as the better-than-average effect), and as the overprecision in one's beliefs (which corresponds to miscalibration). Optimism has a more global description consisting of overestimating the likelihood of positive events and underestimating the likelihood of negative event (Weinstein, 1980). Thus, while overconfidence is a form of optimism, this latter is not a form of overconfidence.

These biases have important consequences on career choices and economic decisions in general (Puri and Robinson, 2007, Astebro et al., 2014). More specifically, the effects on entering entrepreneurship are unambiguous. Camerer and Lovallo (1999) suggest through an experimental approach, that overconfident subjects are entering excessively businesses. De Meza and Southey (1996) state that only optimists become entrepreneurs. Both nascent and existing entrepreneurs perceive the odds of success of their business as significantly higher than historically observed ones (Cooper et al., 1988, Cassar, 2010). Regarding nascent entrepreneurs, they overestimate not only the probability that their venture will be an operating one but also the expected future sales and employment (Cassar, 2010). From a contractual perspective, De Meza and Southey (1996) show that, due to optimism, the equilibrium is characterized by an excess demand for debt over equity. In addition, Landier and Thesmar (2009) argue that entrepreneurial optimism leads to a preference for short-term debt over long-term debt. I take an approach based on contract theory as well in order to analyze how these biases affect investors' decisions to finance entrepreneurs. I consider the financing of those who have already experienced a failure but are either overconfident and/or optimistic.

Getting access to finance after a failure is closely related to the notion of stigma. Being flagged makes it either difficult or costlier to obtain further financing (Landier, 2005, Rodano et al., 2016, Cahn et al., 2021). In Landier (2005), stigma is associated with a conservative equilibrium in which,

after a failure, reentering into the market means supporting higher financial costs. These costs prevent mediocre entrepreneurs from abandoning potentially bad projects and starting again like in an experimental equilibrium. Thus, the stigmatization of failure affects the career choice of failed entrepreneurs who are less likely to initiate again an entrepreneurial activity (Simmons et al., 2014). Incentives to develop entrepreneurial activities are also significantly influenced by bankruptcy laws (Peng et al., 2010, Rodano et al., 2016). Based on the logic of real options theory, Peng et al. (2010) show that entrepreneur-friendly bankruptcy laws may increase incentives to develop entrepreneurial activities. In the same spirit, Rodano et al. (2016) focus on a loan renegotiation reform in Italy and find that more creditor-friendly rules can reduce ex-ante entrepreneurial incentives. Cahn et al. (2021) study the effect of a policy shock related to the traceability of past entrepreneurial failure in France. The authors observe that canceling public reporting of managers involved in corporate liquidations influence positively the entrepreneur's ability to borrow. Hence, stigma exists in some countries, and it plays an essential role in business creation. However, both the efficiency of stigma and the optimal length of public memory are subject to debate in the literature.

If information about past failures is never removed when stigma exists, no one will benefit from a second chance to start a business. This might be inefficient in the case where failed entrepreneurs want to start again with good projects, especially when their past failures are due to bad luck or when they learned from their experience. On the contrary, if their failure is due to their low ability, losing track of past history may be responsible of the bad allocation of resources. Elul and Gottardi (2015) develop a model of repeated borrowing and lending in which they identify an optimal length of memory. Similarly, Kovbasyuk and Spagnolo (2018) focus on a dynamic market game with feedback and determine an optimal length for negative feedback memory. Musto (2004) questions the long term effects and shows that deleting negative information boosts creditworthiness but the long-term effect is reversed and worsened. Regarding the consequences of more or less stigma on the quality of new activities, there is still space for future research. Cahn et al. (2021) underline, in their study, that the probability of default is higher for restarters. They argue that banks rationally use information about failure to make decisions. On the other side, the literature on innovation supports that tolerance for failure is essential to motivate innovation (Manso, 2011). Tian and Wang (2014) establish that companies backed by more failure tolerant venture capitalists are more innovative. Nanda and Rhodes-Kropf (2017) complement these studies by focusing on the nature of the innovation. They underline that radical innovations are more likely to be funded

by failure intolerant investors.

Hence, if the literature provides some evidence about the stigma of failure and its consequences, there is no research combining it with behavioral biases. Nevertheless, entrepreneurs may remain or even become overconfident/optimistic after a failure. If they believe that they acquired some experience and learned from their failure, this might help them increase their self-confidence. If they already were overconfident, the denial of responsibility, accurately or due to a self-attribution bias, may help preserve prior beliefs. Also, as failure represents a serious threat for the social image in some cultures, entrepreneurs may engage in ego-defensive strategies to protect their self-esteem (Dutton and Brown, 1997) or their self-confidence (Bénabou and Tirole, 2002). Such strategies alleviate at least part of the negative consequences of a failure on their social image. Impression management is another strategy that may help maintain relations with external stakeholders by partially accepting the responsibility of the failure. Such attitudes give the illusion that the failed entrepreneur keeps the control, is aware of what happened and can learn from this experience. Thus, behavioral biases may play a role in obtaining financing after a failure.

2.3 Theoretical set-up

To study the stigma of failure, I analyze the decision of an investor to finance the project of a first-time entrepreneur (E) or the one of an E who already failed in the past. Under the assumption that both projects are similar in all respects ³, stigma appears if the investor prefers to finance the first-time E rather than the failed one. The investor's decision is mainly driven by financial incentives. Non-monetary benefits from funding a first-timer or a failed E are not considered. If the project of the new entrant is of higher quality, financing the new entrant will not be regarded as stigmatization of failure for the failed E. Indeed, if an E who failed in the past, does not have access to finance, or if she has to pay more to get it, this may either be due to her past failure or it may be due to her actual type. In the first case, we can claim that there is stigma, while in the second case, there is no stigma. What determines the existence of stigma is the investor's decision when the history of E is private information. If E would have been refused access to finance, in all cases, then stigma does not play any role here, and this situation could be socially desirable. However, if being aware of this past failure drives the investor's decision, E is stigmatized due to

³The main difference between the two E is their respective history.

her failure.

To analyze the investor's preferences, I first identify the optimal contract offered by the investor to E. Depending on the characteristics of this contract, I study if the investor prefers contracting with a first-time E or a failed E. The model developed hereafter presents a simple moral hazard problem from which I derive the optimal contract. The success probabilities reflect the history of E and her subjective beliefs. Thus, the framework exposed in this section is general.

There is one period, and at the beginning of the period, an investor makes a take-it-or-leave-it contract offer to a penniless entrepreneur (E) who wants to start a project requiring an investment I . E may be a new entrant or an experienced E. Once the project is funded, E may behave (here, I especially refer to making an effort) or misbehave (shirk). While misbehaving reduces the success probability of the project, it enables E to get a private benefit B . If E behaves, the project will succeed with probability p_H , otherwise the success probability falls to p_L . These probabilities are the objective ones from which both the investor and E could deviate. I suppose that they agree to disagree when their subjective beliefs are different. At the end of the period, the project generates a revenue R_H if it succeeds and $R_L < R_H$ if it fails. The contract specifies how the revenue is shared between E and the investor. E receives S_H in case of success and S_L in case of failure, while the investor gets $R_H - S_H$ and $R_L - S_L$, respectively. I assume that the revenue is positive even in the case of failure. However, the project remains risky. In addition, the project's NPV is negative when E misbehaves. All agents are risk-neutral, and the discount rate is normalized to zero.

Assumption 1 *The project is risky: $0 < R_L < I$*

Assumption 2 $p_L R_H + (1 - p_L) R_L + B - I < 0$

2.4 Rational benchmark

I define the homogeneous beliefs set-up with objective probabilities as a benchmark. Such a particular case appears when objective probabilities are common knowledge. It also emerges when the investor and E properly assess these probabilities, that is, when their subjective probabilities are identical to the objective ones. These probabilities capture all potential knowledge or experience acquisition/loss related to any past venture. They reflect the actual ability of E at the time of contracting.

Under the assumption that the investor and E do not hold wrong beliefs, the investor's problem is as follows:

$$\begin{aligned}
 & \max_{S_H, S_L} p_H(R_H - S_H) + (1 - p_H)(R_L - S_L) - I \\
 \text{st} \quad & \\
 & p_H S_H + (1 - p_H) S_L \geq p_L S_H + (1 - p_L) S_L + B \quad (IC_E) \\
 & p_H S_H + (1 - p_H) S_L \geq 0 \quad (PC_E) \\
 & R_H \geq S_H \geq 0, \quad R_L \geq S_L \geq 0 \quad (LL)
 \end{aligned}$$

The incentive compatibility constraint of E, denoted (IC_E) , ensures that E provides effort. By rewriting it, we can derive the additional share required by E in case of success compared to the case where the project fails. The participation constraint, (PC_E) , states the minimum amount of revenue required by E to accept the contract. Here, as I assume that E is wealthless, as long as her expected profit is non-negative, she will accept the contract. Considering the limited liability constraints (LL) and (IC_E) , it is straightforward to see that (PC_E) is not binding. Therefore, the optimal contract is a debt-like contract.

Lemma 1 *Under objective beliefs, the optimal contract is a debt-like contract such that $S_H^* = \frac{B}{\Delta p}$ and $S_L^* = 0$.*

In this benchmark case, as the investor and E share the same objective beliefs, there is no reason for E to feel stigmatized. If both types of E have the same skill level, the investor perceives them identically. The investor's problem remains the same, no matter the history of E. Therefore, the proposed contract is identical and the resulting expected profit does not change when financing one or the other. Thus, the investor will not exhibit a preference towards the new entrant relative to the failed E. The only reason he will not invest in E's project after a failure is an insufficient skill. In this case, neither the new entrant nor the experienced E will obtain financing. If the investor prefers one over the other, it is due to a difference in their actual ability⁴ and there is no stigma. The investor refuses access to finance for the failed E due to her actual ability and not

⁴ Δp is higher for the most skilled E, so the investor could not exhibit a preference for the least skilled E due to Δp .

due to her past failure. This is especially optimal from a social point of view when the ability of E is such that the project's NPV is negative despite her effort.

Proposition 1 *When the investor and E hold objective beliefs, there is no stigmatization of failure.*

2.5 Deviation from objective beliefs

2.5.1 Definitions

Since I focus on subjective probabilities in this set-up, both the investor and E are allowed to deviate from objective probabilities. Hence, they can underestimate, overestimate, or properly assess objective probabilities. I explicitly distinguish optimism/pessimism from overconfidence/underconfidence. Optimism (pessimism) refers to the overestimation (underestimation) of success probability regardless of one's behavior (effort or not). As far as overconfidence (underconfidence) is considered, it consists of the overestimation (underestimation) of one's actual ability or performance.

In the model, effort is assumed to be valuable for success. Providing effort increases the probability of success from p_L to p_H . Thus, the difference between p_H and p_L , denoted Δp , reflects E's contribution to success through her effort. We can also define p_H as $p_H = p_L + \Delta p$ with Δp being the increase in success probability due to E's effort. When E is overconfident, she overestimates Δp and perceives it as $\tilde{\Delta p} = \Delta p + \theta$ with $\theta > 0$ being her degree of overconfidence. On the contrary, when E is underconfident, she undervalues her contribution, and $\theta < 0$ captures her underconfidence. No matter the nature of her bias, I suppose that she always perceives providing an effort as more valuable than shirking to succeed. This is different from her perception of utility or expected payoff which includes a private benefit when she shirks.

Assumption 3 $\forall \tilde{p}_L > 0, \tilde{p}_H > \tilde{p}_L$ and $\theta \in] - \Delta p; 1 - \Delta p[$.

If E overestimates (underestimates) the probability of success regardless of the effort she provides, that is, the baseline success probability captured by p_L , she is defined as optimistic (pessimistic). Her perceptions of p_L and p_H become $\tilde{p}_L = p_L + \theta_L$ and $\tilde{p}_H = p_L + \theta_L + \Delta p = p_H + \theta_L$

where $\theta_L \in [-p_L, 1 - p_L]$. Optimism (pessimism) does not exclude overconfidence or underconfidence. E may be both optimistic (pessimistic) and overconfident or underconfident. If, in addition to overestimating (underestimating) the baseline success, she also overvalues (undervalues) her contribution to success, she is both optimistic (pessimistic) and overconfident (underconfident). In this general case, we observe $\tilde{p}_L = p_L + \theta_L$ and $\tilde{p}_H = p_L + \theta_L + \Delta p + \theta = p_H + \theta_H$ where $\theta = \theta_H - \theta_L$. In the remainder of the chapter, as long as $\theta > 0$ ($\theta < 0$), I will refer to E as overconfident (underconfident), even though she is optimistic or pessimistic as well. I will use optimism and pessimism only in the absence of overconfidence/underconfidence.

Definition 1 *Optimistic (pessimistic) E*

E is optimistic (pessimistic) if she overestimates (underestimates) p_L by θ_L , the degree of optimism (pessimism), such that $\tilde{p}_L = p_L + \theta_L$ and $\tilde{p}_H = p_H + \theta_H$ with $\theta_H = \theta_L > 0$ (< 0).

Definition 2 *Overconfident (underconfident) E*

E is overconfident (underconfident) if she overestimates Δp by θ , the degree of overconfidence (underconfidence), such that $\tilde{p}_H = p_H + \theta_H = \tilde{p}_L + \tilde{\Delta p}$ with $\tilde{\Delta p} = \Delta p + \theta$ and $\theta = \theta_H - \theta_L$. For $\theta_L = 0$, E is overconfident (underconfident) only. Otherwise, she is also subject to an optimism (pessimism) bias.

While E could be defined as overconfident (underconfident) or optimistic (pessimistic), the investor may only be optimistic (pessimistic). Indeed, the investor does not provide any effort in this simple moral hazard set-up. As the investor essentially cares about the probability of success when E behaves, I denote his subjective probability $p_I = p_H + \gamma$ in this case, with $\gamma \in [-p_H; 1 - p_H]$. His perception of p_L is denoted $p_L^I = p_L + \gamma_L$. Thus, the investor believes E to increase the probability of success by $\Delta p + \gamma_I$ (with $\gamma_I = \gamma - \gamma_L$) when providing an effort. Here again, I consider that $\Delta p + \gamma_I > 0$ to maintain the moral hazard problem.

Definition 3 *Optimistic (pessimistic) investor*

The investor is optimistic if he perceives p_H as $p_I = p_H + \gamma$ with $\gamma > 0$. He is pessimistic if $\gamma < 0$.

The definition of optimism (pessimism) provided here actually refers to overall optimism (pessimism). Indeed, in a moral hazard context, the investor wants to convince E to make an effort and cares only about p_H to maximize his profit. Therefore, no matter his beliefs about the baseline success (p_L) and E's contribution to success (Δp), as long as he overvalues (undervalues) p_H , he will be defined as optimistic (pessimistic). Thus, he may be considered as optimistic (overall) while undervaluing E's contribution to success if he overvalues the baseline success enough, i.e. $\gamma_L > |\gamma_I|$. Similarly, he may be optimistic overall by being pessimistic about the baseline success but optimistic about E's contribution to success.

Having exposed in the previous section the benchmark case where the investor and E properly assess the objective probabilities, i.e., when they are rational, let's now consider the optimal contract under subjective beliefs.

2.5.2 Optimal contract

When objective probabilities are not common knowledge, individuals try to estimate them and rely on the resulting subjective probabilities to make decisions. In a general framework where both the investor and E hold subjective beliefs and where I do not make any assumption about the direction of their deviation from objective beliefs, the investor's problem is as follows:

$$\begin{aligned}
 & \max_{S_H, S_L} p_I(R_H - S_H) + (1 - p_I)(R_L - S_L) - I \\
 \text{st} \quad & \\
 & \tilde{p}_H S_H + (1 - \tilde{p}_H) S_L \geq \tilde{p}_L S_H + (1 - \tilde{p}_L) S_L + B \quad (IC_E) \\
 & \tilde{p}_H S_H + (1 - \tilde{p}_H) S_L \geq 0 \quad (PC_E) \\
 & R_H \geq S_H \geq 0, \quad R_L \geq S_L \geq 0 \quad (LL)
 \end{aligned}$$

As in the benchmark case, the incentive compatibility constraint of E, denoted (IC_E), ensures that E provides effort. By rewriting it, we can derive the additional share required by E in case of success compared to the case where the project fails. The participation constraint, (PC_E), states the minimum amount of revenue required by E to accept the contract. Here, as I assume that E is wealthless, as long as her expected profit is non-negative, she will accept the contract. Considering

the limited liability constraints (LL) and (IC_E) , it is straightforward to see that (PC_E) is not binding. Also, I exclude the case where E is so underconfident that she thinks to have more chances to succeed by not working (i.e $\tilde{p}_H < \tilde{p}_L$). Indeed, in this particular situation, convincing E to behave requires to give her nothing in case of success while keeping a positive amount for S_L . Therefore, under the assumption that $\theta > -\Delta p$, the optimal contract is again a debt-like contract.

Lemma 2 *Under subjective beliefs, the optimal contract is a debt-like contract such that $S_H^* = \frac{B}{\Delta p + \theta}$ and $S_L^* = 0$.*

The debt-like feature of the optimal contract is not affected by subjective beliefs. The optimal contract remains a debt-like contract irrespective of the biases to which each party is subject. On the contrary, the revenue distribution between the investor and E strongly depends on subjective beliefs. Not all beliefs change the revenue sharing; only E's ones matter. The optimal contract is determined by (IC_E) and the investor's perceptions do not appear there. Rewriting (IC_E) to include the investor's beliefs is possible by expressing E's beliefs with respect to the investor's ones. Nevertheless, the result is still driven by E's perceptions. S_H^* changes with θ , which corresponds to the degree of overconfidence for E. The higher is θ , the lower is S_H^* . Indeed, an overconfident E is convinced by the high likelihood of success when providing effort and requires less. Thus, the agency rent is reduced when contracting with an overconfident E. Such an E ends up with less than what she would get if she was rational ($S_H^* = \frac{B}{\Delta p}$). Nevertheless, due to her bias, she does not perceive it as a low stake since she overestimates her overall expected profit. On the contrary, the more E is underconfident, the more incentives she needs to behave since \tilde{p}_H is closer to \tilde{p}_L . The agency rent increases with underconfidence. Regarding optimism (pessimism), as it concerns both p_H and p_L , the optimal contract is the same as the one offered to the rational E: $S_H^* = \frac{B}{\Delta p}$. Therefore, more than optimism, what matters for contracting here is overconfidence.

Lemma 3 *The optimal contract is only affected by E's subjective beliefs. S_H^* is the same for rational and optimistic (pessimistic) E while it varies with overconfidence.*

Lemma 2 and lemma 3 suggest that being aware of E's subjective beliefs is meaningful for investors. By identifying overconfident E, investors might increase their own profit. The rent they can extract from entrepreneurial overconfidence is $r = \frac{B \cdot \theta}{\Delta p(\Delta p + \theta)}$ with a maximum \bar{r} obtained at the highest

level of overconfidence. However, depending on how biased the investor is, he will differently perceive this rent. Under completely homogeneous beliefs ($p_H = p_I$ and $p_L = p_L^I$), there is no rent extraction from the investor's viewpoint. In this case, they both believe to contract with rational individuals. On the contrary, with heterogeneous beliefs, the value of this rent may be more or less important for the investor. In theory, when the investor knows p_H and p_L , he will be aware of the rent he can extract from E's overconfidence as long as he does not overvalue the contribution of E's effort to success. In practice, the investor will at most learn about p_H and will not be able to dissociate optimism from overconfidence. If he attributes $\theta_H - \gamma > 0$ to overconfidence, then, whenever $p_H > p_I$, the investor will believe to extract a rent. If $\theta_H - \gamma < 0$, the investor will perceive E as underconfident. The only way to increase his profit is to distinguish the least underconfident E. The more pessimistic the investor is, the more he will believe that entrepreneurial overconfidence is prevalent. To increase his profit, he needs to identify the most overconfident E. Hence, even if the investor's beliefs do not change the optimal contract, they significantly affect the financing decisions. Both his perception of E's beliefs ⁵ and his own priors about success are important.

2.5.3 Access to finance with subjective beliefs

To invest in a project, the investor must perceive his own profit as non-negative. Thus, as long as the participation constraint of the investor holds, he may finance a project. His own bias and more specifically, his priors with respect to E will play an essential role in determining his financing decisions. Therefore, it is important to identify under which conditions the investor will generally finance a project, to analyze his preferences better.

Lemma 4 *There are threshold levels of investor pessimism $\underline{\gamma}$ (for the investor) and entrepreneurial underconfidence $\underline{\theta}$ (for E) such that financing is possible iff $\gamma \geq \underline{\gamma}$ and $\theta > \underline{\theta}$ with:*

$$\underline{\gamma} = \frac{I - R_L}{\Delta R - \frac{B}{\Delta p + \theta}} - p_H \text{ and } \underline{\theta} = \frac{B}{R_H - I} - \Delta p$$

Lemma 4 suggests that having too negative beliefs about the success of a project prevents its financing, regardless of which party holds these beliefs. There is a pessimism level under which the investor refuses to finance a project. In addition, E's overconfidence degree is also essential to

⁵In this framework, the investor is perfectly aware of E's beliefs.

identify access to financing. More specifically, we can notice that if $R_H - \frac{B}{\Delta p} < I$, a project is financed only if E is overconfident. In other words, if the investor does not earn enough to cover his investment when E is rational, he will only finance overconfident E, who are more likely to accept lower stakes. For the remainder of the chapter, I assume that $R_H - \frac{B}{\Delta p} > I$ to generalize the results to underconfident E as well.

Unsurprisingly, the project's riskiness makes the financing conditions tougher to satisfy. Indeed, all else being equal, a lower R_L , characteristic of a riskier project, increases the threshold $\underline{\gamma}$. Nevertheless, despite its riskiness, a radical innovation seems to be more likely to obtain financing. By considering that a disruptive innovation supposes an important gap between R_H and R_L , we observe that an increase in ΔR due to a higher R_H , reduces $\underline{\gamma}$. Thus, the financing of radical innovation is even possible with a very pessimistic investor. We can also notice that entrepreneurial overconfidence facilitates the financing of a project. Not only the second condition is satisfied with overconfidence but the first one becomes easier to verify since an increase in θ results in a decrease in $\underline{\gamma}$. Hence, even highly pessimistic investors are more willing to finance overconfident E.

2.6 Stigma of failure

In a subjective beliefs set-up, in addition to the misrepresentation of p_H for a given E, the investor may also hold wrong beliefs about two comparable E. This is particularly true when we compare a first-time E to an E who has already failed. Even though the new entrant and the failed E share the same characteristics (the objective success probability is p_H for both), the investor may perceive them differently. In such a case, the failed E might be stigmatized due to her failure. Thus, through the investor's perception of the failed E, I exogenously introduce the stigmatization of failure in the model. I consider that an investor stigmatizes E if he has a negative and wrong perception of E's ability due to her past failure. I qualify this as a **negative perception of failure** and distinguish it from the **endogenous stigma of failure**. An E is described as stigmatized after a failure if one of the following conditions is verified: (1) the investor prefers to finance the project of a new entrant rather than the one of a failed E, even though their success probability is the same, (2) access to finance is costlier for a failed E due to her past failure. These are observable consequences of being stigmatized, while the negative perception of failure is not necessarily observable. The perception of the investor translates into

observable stigma through his decision. Also, in a sense, it relies on the perceived proportion of good entrepreneurs among failed ones and it is subject to variations.⁶

If, after a failure, E does not have access to finance due to her skill, there is no stigma of failure. Stigma exists only if the financing decision had been different without having any information about E's history. Underestimating the ability of someone due to one's past failure is also a form of stigma. Although it does not result in explicit actions, there is a "social devaluation". That is why, in this chapter, I separately consider the negative perception of failure.

Nevertheless, I do not exclude the possibility of overvaluing the ability of a failed E due to her past failure. Thus, I extend my analysis to situations where the investor overestimates the failed E's ability and has a positive perception of failure. It occurs especially when the investor believes that E acquired some experience or learned from her failure. I also examine the case where, despite holding wrong beliefs, the investor perceives the first-time E and the failed E as equally skilled. In all these situations, the emergence of stigma depends on the investor's preference. The resulting decision, financing or not the failed E, will essentially be determined by the contract offer made to E.

In this section, I identify the conditions under which the stigma of failure appears in an observable form. As before, I consider the investor's choice between financing a first-time E and an E who has already failed. The first-time E corresponds to a fictive benchmark, the objective representation of the failed E who enters the entrepreneurial market for the first time. Namely, they are equally skilled and have the same project characteristics. Hence, their objective probabilities are identical, and the investor should be indifferent between them when deciding whose project to finance. As stated before, this is always the case when objective probabilities are common knowledge. However, when considering deviations from objective probabilities, there are situations in which stigma might emerge.

As there are two types of E, I also suppose that the investor has a specific belief about each of them. I denote p_I^i , the perception he has of the success probability, with $i = N$ for the new entrant and $i = F$ for the failed E. Thus, the decisions of the investor are not only affected by his optimism/pessimism but they are also driven by his beliefs about the new entrant with respect to

⁶What I define as negative perception of failure can be considered as an equivalent of a subjective θ_C or θ_E in the model developed by Landier (2005), i.e., the fraction of good type among failed E. See section 2.6.3 for more details.

the failed E.

2.6.1 When failure is not negatively perceived

There is no implicit stigmatization of failure when the investor has the same perception of the failed E and of the first-timer or when he perceives the failed E as more skilled than a new entrant. Namely, he does not underestimate the ability of the failed E compared to the first timer. We can observe such situations when the investor attributes the failure to external factors. It may also be the case that the investor believes in learning from failure and overvalues the ability of a failed E compared to a new entrant. This can be viewed as a positive stigma of failure. In both cases, failure is not negatively perceived, and stigma appears only subjectively for underconfident E.

Proposition 2 *In the absence of a negative perception of failure, stigma emerges only in a subjective form for underconfident E. The investor even prefers to finance a failed E if:*

- *His perception of failure is positive enough:*

$$p_I^F = p_I^N + \delta > p_I^N \text{ with } \delta \geq -\bar{\delta}$$

- *E is not highly underconfident.*

Proposition 2 states that when the investor perceives a first-time E and a failed E similarly, the failed one does not systematically suffer from the stigma of failure. On the contrary, if she is overconfident, the investor will prefer to finance her compared to the new entrant. This is essentially due to the lower share required by an overconfident E to behave. If she is rational, the investor will be indifferent between financing her or financing the new entrant. In these two cases, there is no stigma of failure. However, if the failed E is underconfident, the investor will prefer to finance the new entrant, and E will suffer from a subjective stigma of failure. Access to finance is not refused to the underconfident E due to her past failure, it is denied because of her bias. In addition, lemma 4 shows that for high levels of underconfidence, the investor will never accept to finance the project, no matter his own perceptions. Therefore, from an objective perspective, there is no stigmatization of failure. This is particularly true if the project's NPV is negative and should not be financed. However, if the investor decides to fund the negative NPV project of the new entrant, the failed one will interpret this decision as a consequence of stigma.

When the investor overestimates the ability of the failed E with respect to the new entrant, the failed E has more chances to be financed. Thus, the stigma of failure is alleviated if the investor overvalues past experience or the ability to learn from failure. Indeed, proposition 2 suggests that even failed E who are underconfident may get access to finance. For this to be possible, two conditions must be satisfied. First, the overestimation of past experience or learning from failure by the investor needs to be higher than the threshold exposed in proposition 2. Then, the degree of underconfidence of the failed E needs to be low enough. However, if the failed E is rational or overconfident, no matter the level of δ , the investor will prefer to finance her rather than the new entrant. Hence, when there is no negative perception of failure, overconfident and rational E seem protected by an observable stigmatization of failure. In contrast, underconfident E can avoid this only if investors put enough weight on past experience and learning from failure. Similarly to the case where $p_I^F = p_I^N$, the preference for a new entrant is not driven by the history of the failed E, it is related to the existence of a high agency rent when contracting with an underconfident E. Therefore, once again, in this context, any direct stigma of failure is only subjective.

Also, notice that if we assume that investors are rational while only E are biased, we fall in this case where there is no negative perception of failure. Indeed, investors do not underestimate the success probability for failed E since they hold objective beliefs. Therefore, the stigma of failure does not exist but underconfident E may still feel stigmatized while they are not. Rational investors, will always prefer to finance overconfident E to maximize their own profit. On the contrary, if we assume that E are rational while investors deviate from objective beliefs, again, as long as there is no negative perception of failure, stigma does not emerge.

2.6.2 From a negative perception of failure to an observable stigma: the role of overconfidence

In this subsection, I concentrate on how the investor's perception of p_H^F and p_H^N influences access to finance through an unobservable stigmatization of failure. Indeed, a failed E also suffers from a stigma of failure when her ability or skill, is underestimated due to her past failure. In this case, when confronting a failed E, the investor systematically underestimates $\Delta p^F = p_H^F - p_L^F$ such that $\Delta p^F = \Delta p + \gamma_I$ with $\gamma_I < 0$. However, observing $\gamma_I < 0$ does not necessarily mean that the investor stigmatizes E for her failure. To be so, we need a comparison with a new entrant.

Therefore, to state that there exists an exogenous stigma, we need to observe that $p_I^N > p_I^F$. I use different notations for investor's pessimism and negative perception of failure to avoid confusion. I suppose that the investor undervalues the ability of the failed E when $p_I^F = p_I^N - \delta < p_I^N$ with δ ⁷ capturing the negative perception of failure. Thus, while stigmatizing E for her failure, the investor does not necessarily undervalue the probability of success. He may be optimistic and perceive p_I^F as higher than p_H even though he underestimates it compared to p_I^N .

When endowed with a negative perception of failure, the investor will be less inclined to provide financing to a failed E compared to a new entrant. In other words, the negative perception of failure will take an observable form through a financing decision: stigma. The following proposition suggests that this stigma may be avoided if the failed E is overconfident.

Proposition 3 *A negative perception of failure does not take the form of an observable stigma if and only if E is overconfident ($\theta > 0$) and δ is below a threshold $\bar{\delta}$ with:*

$$\bar{\delta} = \frac{p_I^N B \theta}{\Delta p (\Delta R (\Delta p + \theta) - B)}$$

Proposition 3 reveals the conditions under which a negative perception of failure results in an observable stigma of failure. It shows that to not be explicitly stigmatized after a failure, two conditions have to hold. First, the negative perception of failure reflected by δ should be moderate enough. Second, E needs to be overconfident. If δ is higher than the given threshold, then an observable stigma of failure will always appear, and the investor will prefer to finance the new entrant. Similarly, any rational or underconfident E will be stigmatized for her failure as long as a negative perception of failure exists. Hence, when investors indirectly stigmatize E for their past failure through their negative perception, entrepreneurial overconfidence protects from the emergence of an observable stigma of failure. We can notice that optimism does not play any role here. Optimism and pessimism do not change the results compared to the rational E case. However, in practice, as it is challenging to distinguish optimism from overconfidence, an investor who perceives an optimistic E as overconfident, may prefer to finance her as well. Thus, depending on the ability of the investor to recognize overconfidence, entrepreneurial optimism may also protect from stigma of failure. Nevertheless, this protection is only objective since the optimistic E will be

⁷ δ corresponds to the difference in the perceived contribution of the first-timer and the failed E, it can be rewritten as $\delta = \gamma_I^N - \gamma_I^F$.

offered a contract intended to an overconfident E. Such a contract proposes a small share to the optimistic E and it could be interpreted by her as stigma as well. Therefore, an optimistic E who gets access to finance after a failure feels still stigmatized. This is also the case for rational and underconfident E who do not obtain financing due to their failure. The resulting stigma, in their case, is objective. The overconfident E will obtain financing due to her biased beliefs that reduce agency rent and increase investor's payoff.

However, even for overconfident E, the financing of radical innovation seems to be difficult. Indeed, any increase in ΔR results in a lower $\bar{\delta}$ and makes the condition tougher to satisfy. This is in line with Nanda and Rhodes-Kropf (2017) suggesting that radical innovation is financed by more failure-intolerant investors. When asking for the financing of radical innovation, the probability to confront stigma is higher even for overconfident E. Thus, my result confirms that investors are less failure tolerant when they have to finance radical innovation.

2.6.3 The perception of failure

As the perception of failure itself may be determined by entrepreneurial overconfidence, in this subsection, I briefly describe the relationship between failure perception and overconfidence. Considering an extension of the model of Landier (2005), if we suppose that overconfident E misperceive intermediate signals about their ability and always reassess their type as good, they will never be inclined to abandon their project. Therefore, the proportion of good E among failed ones will depend on the proportion of overconfident E among good and bad types. If there is an increase in the fraction of overconfident E among good E, or if overconfidence is a bias specific to highly skilled individuals, we will observe more negative perceptions of failure. On the contrary, if overconfidence is a bias specific to low-skilled individuals or if the probability of being overconfident and of a bad type increases, there will be fewer negative perceptions of failure. In this specific case, entrepreneurial overconfidence is socially undesirable as it encourages the financing of negative NPV projects. Thus, proposition 4 raises the question of the existence of a Dunning-Kruger effect for entrepreneurs. If overconfidence is prevalent among low-skilled E, then the positive effects of overconfidence on stigma are reinforced. In contrast, if overconfidence is dominant among high-skilled E, the positive effects of overconfidence on stigma will be reduced.

Proposition 4 *The negative perception of failure is strengthened with the proportion of high-skilled overconfident E and softened with the proportion of low-skilled overconfident E.*

2.7 Project quality with subjective beliefs

Deviation from objective beliefs significantly affects the quality of the projects financed. In this section, I first discuss the consequences of investors' misperception of objective probabilities and then explain how detrimental the confusion between optimism and overconfidence might be.

As investors may overestimate or underestimate the objective probabilities, there is a risk for them to misperceive the NPV of the projects and their expected profit. Thus, investors' deviation from rationality explains some socially suboptimal decisions. More specifically, if investors are pessimistic, they will refuse to finance even good projects and this will cause an underfinancing of such projects. On the contrary, if they are optimistic, there is a risk for them to finance negative NPV projects. Such investors perceive their profit as non-negative while it actually is. This situation is only profitable for E in case of success as she will receive a positive payoff. Hence, while optimism results in excess financing with a risk of accepting negative NPV projects, pessimism leads to an underfinancing of positive NPV projects. This makes entrepreneurial overconfidence socially desirable when investors are highly pessimistic and less desirable when investors are optimistic.

Proposition 5 *Entrepreneurial overconfidence reduces the underfinancing of good projects due to investors' pessimism. However, it fosters excessive financing caused by investors' optimism, making the financing of negative NPV projects more likely.*

When investors are highly pessimistic, they will accept to finance neither the first-time nor the failed E. From the failed E perspective, this cannot be interpreted as a stigma of failure since the new entrant does not have access to finance either. Such a situation is particularly desirable for negative NPV projects that should not get financing. Similarly, a negative perception of failure is socially desirable when the project's NPV is negative. However, wrongly perceiving the ability of a failed E does not prevent an investor from remaining optimistic about the project of a new entrant. In this case, we fall again into a socially suboptimal situation.

Another situation that makes the financing of negative NPV projects more likely is the confusion between optimism and overconfidence. If an investor accepts to finance an optimistic E by

thinking that she is overconfident, he will offer her the contract designed for overconfident E. As long as the participation constraint of the optimistic E holds, she will accept it. Knowing that the share proposed by the investor is not enough to give her incentives to behave (see lemma 2), E will not provide enough effort for the success of the project. Thus, the investor ends up financing a negative NPV project. As a consequence, the likelihood of failure should be stronger for the projects of failed E who are optimistic.

2.8 Business cycles, access to finance and stigma of failure

So far, the results point out essentially the importance of investors' beliefs for the whole level of financing in an economy and for the stigmatization of failure. At the same time, E's biased beliefs may benefit investors and play an interesting role in refinancing failed E despite an existent stigma of failure. Knowing that both beliefs and objective values are sensitive to business cycles, it is interesting to analyze the previous results from a macroeconomic perspective. More specifically, economic conditions may explain the level of optimism/pessimism for investors and E. They can also change the objective probability of success for a good project ($p_H \pm \tau$) or the level of revenues ($R_H \pm r_H$ or $R_L \pm r_L$). However, whether entrepreneurial overconfidence would vary or not with business cycles is less clear. As optimism is a broader concept than overconfidence, we can expect E to become more or less optimistic with economic conditions. Nevertheless, this does not necessarily mean they are more or less overconfident. Therefore, when discussing my results, I only consider optimism as sensitive to business cycles.

The conditions to obtain financing for a project become easier to verify during good times compared to bad times for two reasons. First, as suggested by some studies, investors' beliefs tend to be extrapolative (Greenwood and Shleifer, 2014). Investors may be less pessimistic during booms, especially if they are myopic. Thus, the condition $\gamma \geq \underline{\gamma}$ from lemma 4 is easier to satisfy. Second, if investors' biases remain unaffected, expectations about R_H , and even R_L , fluctuate with the business cycle. Indeed, under good economic conditions, it is easier to imagine that a project will generate more revenue than during recessions. Therefore, an increase in expected R_H or R_L , all else being equal, reduces $\underline{\gamma}$. An increase in the objective probability p_H has the

same effect. Although investors do not change their beliefs following the business cycle, the first condition of lemma 4 becomes easier to satisfy. This is also true for the second condition related to entrepreneurial overconfidence. In good times, E who remain highly underconfident can also obtain financing since an increase in R_H results in a decrease of $\underline{\theta}$. Hence, even pessimistic investors are more likely to accept financing in good times. On the contrary, periods of recessions make financing conditions tougher to satisfy. But what about the stigmatization of failure during booms and busts? Should we expect failure to be less stigmatized in good times compared to bad times?

Following propositions 3 and 2, to avoid the stigmatization of failure, either the investor should not have a negative perception of failure, or, if it is moderate, E has to be overconfident. The negative perception of failure is softened when a project's success seems less dependent on E's effort. If good times appear to be more favorable to success overall or to the luck factor, then investors will be less attentive to past failures, and we should observe less stigma. If they still care about past failures despite good economic conditions, having a higher $\bar{\delta}$ makes entrepreneurial overconfidence more useful against stigmatization. Indeed, a higher $\bar{\delta}$ means that more pronounced negative perceptions of failure may be balanced by overconfidence to not result in an observable stigma. This occurs when all else being equal, p_I^N increases, that is when p_H is higher or when investors are more optimistic. Hence, a failed E has fewer chances to confront stigma if she decides to start her new venture during a period of expansion. This also raises the question of the good timing for abandoning a venture. Strategic timing of failure may be helpful in avoiding negative effects from wrong perceptions of failure.

Lastly, the literature on venture capital provides evidence that investors try to manage their performance for reputation purposes in several ways (Barber and Yasuda, 2017, Chakraborty and Ewens, 2018). Delaying failures until raising a new fund is one of them (Chakraborty and Ewens, 2018). However, there no study suggests that E times their failure to protect their reputation as well, especially in countries where stigma is part of the culture. When investors' performances are in play, timing a failure is a strategy that may benefit both investors and E. Waiting until a crisis to fail may be a way to avoid the stigma of failure. Indeed, failures that occur during a crisis will be less frequently attributed to one's ability since such periods are also favourable to failures of good types. Thus, when E fail during bad times, the information revealed about one's type is less precise and reliable. Negative perceptions of failure and, as a consequence, stigmatization should not appear much when a failure occurs during bad economic conditions. We should therefore

observe that part of failures during recessions are strategic.

2.9 Conclusion

At first glance, being overconfident seems detrimental to E since they will receive a lower share relative to unbiased ones. However, I show that, at the same time, this bias enables them to have easier access to finance compared to rational E. More specifically, I underline that this is also the case for failed E. Overconfidence protects failed E from being stigmatized for their failure. In a world where objective beliefs are common knowledge, the stigma of failure does not exist. However, in our world, it does and it exists both subjectively and objectively. Its emergence is essentially related to investors' perception of E's failure. An investor who underestimates the true ability of a failed E and undervalues it compared to a new entrant, indirectly stigmatizes her. If, in addition, he refuses to finance her due to her failure, he directly stigmatizes her.

I show that when investors do not have negative perceptions of failure, the stigma emerges only subjectively and for underconfident E. When investors overvalue past experience and/or the ability to learn from failure, they may even prefer contracting with a failed E rather than a first-timer. This is what we observe in countries considering failure as a stepping stone to future success. In contrast, when they perceive failure negatively, stigma appears objectively for both underconfident and rational E. If this perception of failure is moderate enough, I find that entrepreneurial overconfidence is essential to avoid observable stigma. This result does not hold for optimism. However, from an empirical perspective, optimism should also protect from stigma since disentangling these two notions is difficult for investors. Hence, one of the main prediction of this chapter is that overconfident and optimistic E who have already experienced a failure are more likely to obtain financing for their new ventures. Also, as overconfidence may balance the negative effects of the stigma of failure, we can think of overconfidence as a starting point for the experimentation culture.

Another consequence of the confusion between optimism and overconfidence concerns investors' profit. If an investor accepts to finance an optimistic E by thinking that she is overconfident, he will offer her the contract designed for overconfident E and end up financing a negative NPV project. Therefore, the likelihood of failure should be stronger for failed E who are optimistic. The financing of negative NPV projects is also explained by the investor's own perception of

success probability. When deviating from objective beliefs, he increases the risk of making socially undesirable decisions. His own optimism will contribute to the financing of negative NPV projects, while his pessimism will avoid the financing of good projects. Thus, high degrees of optimism, both for investors and E, increase the likelihood of financing negative NPV projects. At the same time, entrepreneurial overconfidence plays an additional interesting role as it reduces the underfinancing of good projects attributed to investors' pessimism. Indeed, even highly pessimistic investors may be inclined to fund the projects of overconfident E.

Considering that economic conditions may substantially influence beliefs, it is interesting to discuss how they affect the degree of stigmatization as well. Failures that occurred during bad economic conditions should be less subject to stigma since investors and E are more likely to attribute such failures to external factors. This is particularly true for the Covid crisis during which some closures were inevitable. Hence, investors might be less prone to underestimate the ability of an E who failed during a period of crisis compared to a first-timer. Similarly, E who failed during economic downturns, should not lose confidence. As a result, the stigmatization of failure is expected to be reduced after such periods and E aware of that may be prone to strategically delay their failures until recessions. Hence, we should empirically observe that E who experienced their failures during economic downturns are more likely to be financed again. During crises, considering investors pessimism, the fraction of failed E among those who obtained financing should be lower compared to other periods. At the same time, the level of entrepreneurial overconfidence or optimism is expected to be particularly high for E who have access to finance during periods of crisis.

2.10 Proofs

Proof of Lemma 1

Lemma 1 states that under objective beliefs, the optimal contract is a debt-like contract such that that $S_H^* = \frac{B}{\Delta p}$ and $S_L^* = 0$.

The investor's problem can be rewritten as follows:

$$\begin{aligned} & \max_{S_H, S_L} p_I(R_H - S_H) + (1 - p_I)(R_L - S_L) - I \\ \text{st} \quad & \Delta S \geq \frac{B}{\Delta p} & (IC_E) \\ & p_H \Delta S + S_L \geq 0 & (PC_E) \\ & R_H \geq S_H \geq 0, \quad R_L \geq S_L \geq 0 & (LL) \end{aligned}$$

For IC_E to hold, ΔS must be positive since $\frac{B}{\Delta p}$ is strictly positive. Indeed, I assume that $\Delta p > \theta$ since otherwise the moral-hazard issue disappears and the investor is sure that E will not provide any effort. If PC_E binds, considering the limited liability constraints, IC_E is violated. However, when IC_E binds, PC_E holds and the optimal contract is such that $\Delta S^* = \frac{B}{\Delta p}$. Here we can consider that maximizing the profit of the investor is the same as minimizing the profit of E: $p_I \Delta S + S_L$ while $\Delta S^* = \frac{B}{\Delta p}$ implies that $S_L = 0$. This does not violate the limited liabilities constraints. Hence, the optimal contract is such that $S_L^* = 0$ and $S_H^* = \frac{B}{\Delta p}$. This is a debt-like contract since the investor receives all the revenue if the project fails.

Proof of Lemma 2

Lemma 2 states that under subjective beliefs, the optimal contract is a debt-like contract such that $S_H^* = \frac{B}{\Delta p + \theta}$ and $S_L^* = 0$.

As in the previous proof, we can rewrite IC_E and PC_E under subjective beliefs as follows:

$$\begin{aligned} \Delta S & \geq \frac{B}{\Delta p + \theta} & (IC_E) \\ \tilde{p}_H \Delta S + S_L & \geq 0 & (PC_E) \end{aligned}$$

As the optimal contract is such that IC_E binds, we have $\Delta S^* = \frac{B}{\Delta p + \theta}$. Again, minimizing $p_I \Delta S + S_L$ while $\Delta S^* = \frac{B}{\Delta p + \theta}$ implies that $S_L = 0$. This does not violate the limited liabilities constraints. Hence, the optimal contract is such that $S_L^* = 0$ and $S_H^* = \frac{B}{\Delta p + \theta}$.

Proof of Lemma 3

Lemma 3 explains that the optimal contract is only affected by E's subjective beliefs. Entrepreneurial rationality and optimism (pessimism) result in an identical optimal contract while the degree of overconfidence (underconfidence) changes it.

From Lemma 2, we know that the optimal contract is such that IC_E is binding. As neither the investor's beliefs nor the degree of entrepreneurial optimism appear in IC_E , the contract is only affected by E's subjective probability. Indeed, the contract is such that: $S_L^* = 0$ and $S_H^* = \frac{B}{\Delta p + \theta}$ where S_H is a function of θ , the overconfidence level of E. The degree of optimism/pessimism does not appear since optimism corresponds to an overestimation of both p_H and p_L by θ_L . It does not change the value of Δp and the contract remains similar to the rational case where $\theta = 0$. A rational and an optimistic (pessimistic) E are offered the same contract $S_H^* = \frac{B}{\Delta p}$.

Proof of Lemma 4

Lemma 4 defines the conditions under which a project is financed. A project is not financed if the investor is too pessimistic or if E is too underconfident. There are threshold levels of investor pessimism $\underline{\gamma}$ (for the investor) and entrepreneurial underconfidence $\underline{\theta}$ (for E) such that financing is possible iff $\gamma \geq \underline{\gamma}$ and $\theta > \underline{\theta}$ with:

$$\underline{\gamma} = \frac{I - R_L}{\Delta R - \frac{B}{\Delta p + \theta}} - p_H \text{ and } \underline{\theta} = \frac{B}{R_H - I} - \Delta p$$

The investor participates in a project, that is he accepts to finance it, if and only if his expected profit is non-negative. Considering his subjective beliefs, the investor perceives his expected profit as:

$$\Pi_I = (p_H + \gamma)(R_H - \frac{B}{\Delta p + \theta}) + (1 - (p_H + \gamma))R_L - I$$

We then have:

$$(p_H + \gamma)(R_H - \frac{B}{\Delta p + \theta}) + (1 - (p_H + \gamma))R_L - I \geq 0$$

$$(p_H + \gamma)(\Delta R - \frac{B}{\Delta p + \theta}) \geq I - R_L \quad (2.1)$$

Knowing that $I - R_L$ is strictly positive, (2.1) holds only if $\Delta R - \frac{B}{\Delta p + \theta} > 0$. This gives us a minimum level θ , under which the investor does not finance the project of E. Put differently, access to finance requires $\theta \geq \frac{B}{\Delta R} - \Delta p$.

At the same time, as $\Delta R - \frac{B}{\Delta p + \theta} \geq (p_H + \gamma)(\Delta R - \frac{B}{\Delta p + \theta})$, (2.1) implies that $\theta \geq \frac{B}{R_H - I} - \Delta p$. This is a narrower condition on θ since $I > R_L$. Therefore, the minimum level of θ required to get financing is given by: $\theta \geq \frac{B}{R_H - I} - \Delta p$. Written differently, this condition shows whether or not the investor will get back the committed amount when contracting with such an E. If E is too underconfident, she needs such a high stake to behave that $R_H - \frac{B}{\Delta p + \theta} < I$ and the investor loses money with such an investment.

Then, the condition we get on γ is as follows:

$$\gamma \geq \frac{I - R_L}{(\Delta R - \frac{B}{\Delta p + \theta})} - p_H$$

Knowing that $\gamma \in [-p_H; 1 - p_H]$, we need to verify if the rhs is in the same interval. It is straightforward to see that this inequation is not always satisfied since the rhs is higher than $-p_H$. Hence, this is a necessary condition. To have the rhs lower than $1 - p_H$ we need $\theta > \frac{B}{R_H - I} - \Delta p$.

Proof of Proposition 2

Proposition 2 suggests that in the absence of a negative perception of failure, stigma emerges only in a subjective form for underconfident E. The investor even prefers to finance a failed E if:

- His perception of failure is positive enough:

$$p_I^F = p_I^N + \delta > p_I^N \text{ with } \delta \geq -\bar{\delta}$$

- E is not highly underconfident.

The absence of a negative perception of failure supposes that either $p_I^F = p_I^N = p_I$ or $p_I^F > p_I^N$. An observable stigma of failure does not emerge if the investor does not exhibit a preference for the new entrant's project. Such a preference comes from the comparison of his expected profit in each situation.

Thus, when $p_I^F = p_I^N = p_I$, the investor prefers to finance the failed E or he remains indifferent between financing her project or the one of the new entrant if and only if $\Pi_I^F \geq \Pi_I^N$. This condition is satisfied iff $\theta \geq 0$:

$$p_I(\Delta R - \frac{B}{\Delta p + \theta}) \geq p_I(\Delta R - \frac{B}{\Delta p})$$

$$\theta \geq 0$$

For $\theta = 0$, the investor is indifferent between the two projects and the stigma of failure does not emerge either. Thus, only underconfident failed E are refused access to finance when the investor needs to choose between a failed E and a new entrant.

When $p_I^F = p_I^N + \delta > p_I^N$, even underconfident E may be preferred to first-time entrepreneurs and the stigma of failure is alleviated. The investor prefers to finance the failed E if:

1. He is enough optimistic about the ability of the failed E: $\delta \geq \frac{-p_I^N B \theta}{\Delta p(\Delta R(\Delta p + \theta) - B)}$.
2. The failed E perceives p_H s.t : $\theta \geq \frac{(1 - p_I^N)(B - \Delta p \Delta R)\Delta p}{B p_I^N + (1 - p_I^N)\Delta R \Delta p}$

Indeed, the investor prefers to finance the failed E or remains indifferent iff $\Pi_I^F \geq \Pi_I^N$:

$$(p_I^N + \delta)(\Delta R - \frac{B}{\Delta p + \theta}) \geq p_I^N(\Delta R - \frac{B}{\Delta p})$$

$$p_I^N(\frac{B}{\Delta p} - \frac{B}{\Delta p + \theta}) + \delta(\Delta R - \frac{B}{\Delta p + \theta}) \geq 0 \tag{2.2}$$

From lemma 4, we know that $\Delta R \geq \frac{B}{\Delta p + \theta}$, otherwise the investor does not consider the project for financing. When $\theta \geq 0$, (2.2) always holds. As $\theta \in (-\Delta p, 1 - \Delta p]$, we need to identify more general conditions under which (2.2) is satisfied. By modifying a bit the inequality, we obtain:

$$\delta \geq \frac{-p_I^N B \theta}{\Delta p (\Delta R (\Delta p + \theta) - B)} = -\bar{\delta}$$

As $\delta \in [0; 1 - p_I^N]$ we need to verify that:

$$\frac{-p_I^N B \theta}{\Delta p (\Delta R (\Delta p + \theta) - B)} \leq 1 - p_I^N$$

$$\theta \geq \frac{(1 - p_I^N)(B - \Delta p \Delta R) \Delta p}{B p_I^N + (1 - p_I^N) \Delta R \Delta p}$$

The rhs is always higher than $-\Delta p$ and lower than $1 - \Delta p$, so this condition is required to avoid the emergence of a direct stigma of failure. Note that this threshold is negative.

Proof of Proposition 3

According to Proposition 3, a negative perception of failure does not take the form of an observable stigma if and only if E is overconfident ($\theta > 0$) and δ is below a threshold $\bar{\delta}$ with:

$$\bar{\delta} = \frac{p_I^N B \theta}{\Delta p (\Delta R (\Delta p + \theta) - B)}$$

When $p_I^F \neq p_I^N$ and $p_I^F = p_I^N - \delta < p_I^N$, the investor prefers to finance the failed E or remains indifferent if $\Pi_I^F \geq \Pi_I^N$:

$$(p_I^N - \delta) \left(\Delta R - \frac{B}{\Delta p + \theta} \right) \geq p_I^N \left(\Delta R - \frac{B}{\Delta p} \right)$$

For $\Delta R \geq \frac{B}{\Delta p + \theta}$ we have:

$$\delta \leq \frac{p_I^N B \theta}{\Delta p (\Delta R (\Delta p + \theta) - B)} \quad (2.3)$$

As $\delta > 0$, (2.3) holds only for positive values of θ .

Proof of Proposition 5

Proposition 5 states that entrepreneurial overconfidence reduces the underfinancing of good projects due to investors' pessimism. However, it fosters excessive financing caused by investors' optimism, making the financing of negative NPV projects more likely.

From lemma 4, we know that the investor perceives his expected profit as positive when:

$$\gamma \geq \frac{I - R_L}{\Delta R - \frac{B}{\Delta p + \theta}} - p_H \text{ and } \theta \geq \frac{B}{R_H - I} - \Delta p.$$

For the expected profit of the investor to be positive, the project's NPV has to be positive as well. Otherwise, the expected profit is necessarily negative.

We know that a project's NPV is negative if: $p_H R_H + (1 - p_H) R_L - I < 0$.

Considering that $\frac{B}{\Delta p + \theta} > 0$, the expected profit of the investor is negative as well in this case:

$$p_H \left(R_H - \frac{B}{\Delta p + \theta} \right) + (1 - p_H) R_L - I < 0 \tag{2.4}$$

and the project should not be financed. By modifying a bit (2.4), we find that the expected profit of the investor is negative when: $p_H < \frac{I - R_L}{\Delta R - \frac{B}{\Delta p + \theta}}$.

However, from lemma 4, we know that if this is the case, then $\gamma > 0$, that is, the investor should be optimistic to participate in a project. Hence, when deviating from objective beliefs, there is a risk that the investor accepts to finance a project generating a negative payoff for him. If this does not always imply that the project's NPV is negative, such a situation is not excluded. Thus, as long as the investor accepts to finance a project, i.e, as long as θ is high enough, there is a risk for him to finance a negative NPV project if he is optimistic. On the contrary, if the investor is too pessimistic, he will refuse to finance such a project, even though it is a positive NPV one when

$$p_H > \frac{I - R_L}{\Delta R - \frac{B}{\Delta p + \theta}}.$$

Knowing that the pessimism level under which financing is not possible decreases with entrepreneurial overconfidence, this latter is a good way to avoid the underfinancing of good projects due to investors' pessimism. By contrast, when investors are optimistic, entrepreneurial overconfidence increases the likelihood of funding and thus, the risk of financing negative NPV projects.

Chapter 3

Serial Entrepreneurship and Experimentation in the US

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Abstract

While the US is widely considered a place where entrepreneurs can experiment through trial and error, most of the evidence remains anecdotal. This paper explores how past founder experience affects incentives to start again and financing. It especially sheds light on venture capitalists' (VCs) contribution to reentry into entrepreneurship. The results suggest that VCs celebrate both success and failure for serial entrepreneurs with past VC financing experience and penalize failure for others. However, I do not observe a statistically significant difference between the performance of first-timers and failed entrepreneurs. Thus, there is no performance-related reason to prefer the former or the latter. In addition, I find that serial founders who did not receive any VC financing before are more likely to succeed than those who did.

3.1 Introduction

“And if you did fail, you got up and tried again. And if you failed again, you got up and tried again. And if you failed again, it might be time to think about doing something else. But it was not just success, but not being afraid to fail that brought you to this point”

*John Roberts, Supreme Court Chief Justice
in a commencement speech, June 3, 2017*

In his commencement speech at his son’s graduation, John Roberts, the Supreme Court Chief Justice, encourages graduates to embrace failure and try again. This also reflects the famous Silicon Valley mindset, where entrepreneurial failure is viewed as a stepping stone to success. Since failure is ubiquitous in entrepreneurship, its perception is extremely important in this context. Indeed, as described by Kerr et al. (2014), *“entrepreneurship is fundamentally about experimentation because the knowledge required to be successful cannot be known in advance or deduced from some set of first principles.”* To enable experimentation, it is essential to let people try and try again. In a sense, venture capital (VC) investors, who are important contributors to the creation and development of high-growth potential start-ups, facilitate experimentation. They give chances to multiple ventures until receiving some signals to pursue or not their investments. However, whether and how they help to reenter the entrepreneurial market needs attention.

In Europe, the existence of a negative perception of failure that prevents entrepreneurs from accessing finance, and creating new firms, is already documented (Cahn et al., 2021). In the US, most of the evidence remains anecdotal. Therefore, it is important to investigate how dominant the positive view of failure is, in the US, in an entrepreneurial context. In this chapter, I aim to shed more light on this and explore the contribution of VCs to the experimentation culture. More specifically, I ask if entrepreneurial experience matters more than the outcome for them.

To address this question, I naturally focus on serial entrepreneurship in the US. Letting experienced founders start new ventures again is part of the experimentation process. If successful entrepreneurs convey a positive signal about future performance, the signal sent by unsuccessful entrepreneurs is less clear. While learning from past experiences and errors can help to reach success, bad skills and resilience towards learning would repeat failure. Hence, depending on what is most frequent, there might be rational explanations for the way failure is perceived. This study provides support for both positive and negative views to failure. Nevertheless, according to my

findings, whether rational reasons explain them is still questionable.

I first examine the reasons to believe that, in the US as well, failure can prevent reentry into the entrepreneurial market. One of the difficulties encountered when studying success or failure in entrepreneurship is to define them in a way that fits the perception of entrepreneurs. As these latter are subjective and personal, not everyone has the same definition. Nevertheless, due to my main focus on VC investors and VC financing, I rely on the most common definitions used in the VC literature, i.e., those that capture investors' perceptions. Thus, I consider success as going public or being acquired¹, and regarding failure, I rely on two definitions. A narrow definition considers failure as closing the business without achieving a successful exit. A broader definition accounts for financing termination as failure as well. Hence, it additionally covers operating firms that received any VC or angel financing but that did not obtain funding for more than three years.

By tracking successful and unsuccessful entrepreneurs' careers with Crunchbase data, I identify whether they start a new venture after the exit of the focal one. I find that founders who experienced failure² are, on average, 16 to 35% less likely to start again compared to successful entrepreneurs within the same state and industry³. This is a surprising result for a country where we would not have expected such a gap. Indeed, if failure is positively perceived and experimentation is encouraged, failed entrepreneurs should not have fewer incentives or more financial constraints to start again. At the same time, as recently established by Amornsiripanitch et al. (2022), even failed entrepreneurs have quite interesting outside options. Therefore, it is plausible that preferences for outside options or confidence loss explain the previous finding⁴. Nevertheless, I also find that after experiencing failure, those who start a new venture are more inclined to start elsewhere. Thus, these observations further motivate me to investigate VC fundraising and clarify how failure is perceived and whether VCs foster experimentation in the US.

For that purpose, I would ideally compare serial founders to first-time entrepreneurs with respect to their likelihood of raising VC financing. A key advantage of using Crunchbase data is that, unlike other data sources commonly used to study entrepreneurial finance, it is not restricted to VC-backed companies. Therefore, while prior studies on serial entrepreneurship essentially concentrate on VC-backed firms (Hsu, 2007, Gompers et al., 2010, Bengtsson, 2013, Nahata, 2019),

¹Additional analyses consider only some high-value acquisitions as successes.

²For this part of the study, I use the narrow definition of failure in the main analysis and the broad one in robustness tests.

³Unreported results show that this is not substantially different from what we observe in Europe.

⁴Ongoing research aims to rule out this explanation by exploring further the next job position of failed entrepreneurs.

I take advantage of Crunchbase data to explore access to VC financing. In a comprehensive analysis of second-time entrepreneurs, I find that, although failure is not stigmatized, it is not necessarily perceived positively. Founders who experienced failure in their first venture are not less likely to get VC financing than new entrants. However, they are not more likely to obtain VC financing either. What appears to be valued by VC investors is past success only. Such an experience makes founders, on average, 27% more likely to rely on VC financing relative to first-timers. However, I show that these results should be carefully considered. Looking further among serial entrepreneurs indicates that these findings only hold for some types of serial founders

Indeed, while these findings document neither a negative nor a positive perception of failure, I further show that founders' prior VC financing experience plays an essential role in VCs' perception of past founder experience. Unconditional of the first venture outcome, a second-time founder who has already received VC funding in the first firm will have more chances to raise capital in the focal firm compared to a new entrant. Conversely, for second-time entrepreneurs who were never backed by VCs, past experience, including a successful one, does not increase the probability of obtaining VC financing. On the contrary, the previous failure reduces the likelihood of raising VC financing by 6 percentage points compared to first-timers. Hence, I show that common priors about the experimentation culture and the absence of stigma of failure in the US are not unjustified. However, they are only valid for a specific category of entrepreneurs: those who have already entered the VC circle. Entrepreneurs who never benefited from VC financing might still be penalized for their past failure⁵ while they are not rewarded for their success.

Why would VC investors favor entrepreneurs who previously obtained VC financing and value their experience more than those of other serial entrepreneurs? Prior studies have established that social capital and ties to VCs facilitate access to financing due to informational concerns (Shane and Cable, 2002, Hsu, 2007) although repeated relationships are not frequent (Bengtsson, 2013). It is also possible that such founders learned about VCs and are more likely to persuade them. Indeed, serial entrepreneurs are shown to obtain more favorable contractual terms compared to novice founders (Nahata, 2019), even though only those who experienced success before are found to negotiate higher valuations (Hsu, 2007). However, none of these studies provides insights regarding performance. A reasonable and rational explanation is that serial founders who have already experienced VC financing outperform those who did not. This could be the case for at least

⁵Analysis of performance further clarifies whether they are actually stigmatized or not.

two reasons. First, VCs, known to add value to startups (Hellmann and Puri, 2002, Hsu, 2006, Sørensen, 2007, Bottazzi et al., 2008, Chemmanur et al., 2011, Bernstein et al., 2016, Ewens and Marx, 2018), might also add value to founders. Founders can learn from them unconditionally on the outcome. In the specific case of failed entrepreneurs, VCs may help them notice their mistakes and increase their chances of learning from their errors. Therefore, VCs might be more confident about these founders' potential to learn from failure. Second, this type of founder might originally have the profile of "*the successful entrepreneur*" defined by VCs. As VC investors undergo a selection process, prior VC experience could play a signaling or a certification role on which future investors rely when screening serial founders.

To handle this question and to understand whether the observed funding gap is justified, I examine the future performance of both groups of serial founders. My results reject the value-adding theory of VCs and support that VCs favor previously backed entrepreneurs due to their selection criteria. Nevertheless, I find that such a preference is not justified from a performance perspective. Serial founders who never benefited from VC financing before outperform those who did. Thus, I argue that reducing the differences between the selected profiles might prevent VCs from discovering other characteristics of serial founders that might be essential for success. Overall, these findings suggest that there are valuable investment opportunities among entrepreneurs who have never entered VCs' circle.

At first glance, studying future performance indicates that past outcome matters for it while experience does not. Indeed, I confirm that success breeds success (Gompers et al., 2010), but I do not observe that failure helps to succeed. Regarding future failure, my results show that none of the past outcomes contribute to avoiding it. However, although I do not find support for positively valuing past experience regardless of the outcome, my study does not show that failed entrepreneurs underperform new entrants in terms of future performance. Past failure does not seem to decrease the likelihood of success or increase the probability of future failure. Therefore, there is no apparent performance-related reason to prefer first-timers over failed entrepreneurs, nor a reason to prefer the latter over the former. If such preferences exist, then it means that failure is stigmatized or past experience is overestimated. Results related to past failure experience hold for both groups of serial founders. Those concerning past successful experience are essentially driven by serial entrepreneurs without past VC experience. These latter overperform new entrants more than serial founders who have experienced VC financing before. Besides, the results showing that

the preferred group perform better than first-timers remain weak.

Taken together, my findings support that starting a new venture after a failure is not obvious, even in the US. While I confirm that success breeds success, I also show that failure should not be stigmatized. Nevertheless, the ability of entrepreneurs to learn from failure should not be overestimated either. According to these results, the attitude to adopt is: rewarding past successes without penalizing past failures. Investors should be indifferent between financing new entrants or failed entrepreneurs. However, my study documents that VC investors behave differently. They celebrate both success and failure for a certain type of founders while they stigmatize failure and do not reward success for another group of entrepreneurs. Thus, they push experimentation in one group and restrict it for another category. Nevertheless, I show that the underfinanced group is the overperforming group. My ongoing research at the VC investor level aims to clarify which type of investors are particularly concerned by these findings and whether other investor-related channels help explain these results⁶.

Given that Crunchbase mainly tracks tech companies that seek financing, and has better coverage of companies that received at least one type of financing, my results should not be driven by the fact that serial founders without past VC experience are less prone to request VC financing. Such cases should be limited and probably already excluded from my main sample due to missing information. Nevertheless, I still ensure that the existence of alternative sources of financing do not reduce their likelihood of raising VC financing. I exclude this alternative explanation by running a robustness test where I control for other financing sources such as angel financing, debt financing, and crowdfunding. Despite this, if my results are explained by such founders' reduced incentive to ask for VC financing, they still hold important implications for them. Indeed, in this case, serial founders who escape VC financing might miss opportunities to grow and survive longer. If I do not find that VCs add value to serial founders, I notice that they help them to avoid failure. Thus, if such founders aim to remain operating without necessarily achieving a successful exit, they might benefit from VC financing. If their goal is to go public or get acquired, then, they are already performing well without VCs' support.

This chapter contributes to the literature in many aspects. It first adds to the limited research on serial entrepreneurship. Gompers et al. (2010) focus on the performance of VC-backed serial founders and document the persistence of success in entrepreneurship. Analyzing non-VC-backed

⁶So far, I have already established that serial founders who benefit the most from the experimentation culture, i.e. those with past VC financing experience are more likely to be funded by failure tolerant investors.

sectors, Lafontaine and Shaw (2016) establish that serial entrepreneurs benefit from longer business duration and argue that entrepreneurship is a learned skill. Other studies concentrate on social capital and relational VC financing (Shane and Cable, 2002, Hsu, 2007, Bengtsson, 2013). They show that ties to VCs help to raise VC financing (Shane and Cable, 2002) and to negotiate higher valuations after a past successful experience (Hsu, 2007) although repeated relationships are not common (Bengtsson, 2013). Besides, Nahata (2019) finds that past founder experience helps to contract more favorable deal terms than new entrants. I document differences in access to VC financing and in future performance among entrepreneurs who were previously VC-backed and those who were not. I show that while the latter overperform the former, they suffer from the stigmatization of failure and are not rewarded for past success. While the contribution of social capital to mitigate informational concerns is not negligible, I argue that the screening procedure of VCs motivates them to rely on signals conveyed by previous selections.

This study also fits within the literature on the stigmatization of failure. It provides some evidence about the negative perception of failure in the US, while the existence of stigma is already established in Europe (Cahn et al., 2021, Rodano et al., 2016). Since a cultural revolution that changed the perception of failure in the US (Efrat, 2006), it is more frequently associated with the experimental equilibrium described by Landier (2005), where the willingness to start again is high, and the cost of experimentation is low compared to the conservative equilibrium. However, I show reasons to think that failure might be a barrier to starting again (Simmons et al., 2014), even in the US. Also, I argue that failure should not be stigmatized for performance-related reasons whereas success should be rewarded⁷, I observe that VCs behave differently. They push the experimental equilibrium for some entrepreneurs and the conservative one for others. While their screening process is at play, VCs' failure tolerance (Tian and Wang, 2014) also contributes to explaining such a result. As the perception of failure and access to finance affects entrepreneurial entry, this chapter has also implications for the choice to enter or reenter the entrepreneurial market (Gromb and Scharfstein, 2002, Moskowitz and Vissing-Jørgensen, 2002, Lazear, 2005, Puri and Robinson, 2013, Hurst and Lusardi, 2004, Townsend et al., 2010, Astebro et al., 2014, Hvide and Panos, 2014, Manso, 2016, Levine and Rubinstein, 2017, Catherine, 2022). Therefore, it also adds to studies about experimentation and entrepreneurship more broadly (Manso, 2016, Kerr et al., 2014, Xu,

⁷Here, by performance I refer to successful exits and failures rather than innovation that would require to be more specific about duration. Indeed, Manso (2011) shows that rewarding long-term success and not penalizing short-term failure is a good recipe to motivate innovation.

2018, Chemla and Tinn, 2020).

Lastly, my findings contribute to the venture capital literature. First, they complement studies about VCs' decision making process (Kaplan and Stromberg, 2001, 2004, Kaplan et al., 2009, Bernstein et al., 2017, Gompers et al., 2020). Second, they provide more insights about the value-added of VCs (Hellmann and Puri, 2002, Hsu, 2006, Sørensen, 2007, Bottazzi et al., 2008, Chemmanur et al., 2011, Bernstein et al., 2016, Ewens and Marx, 2018).

The remainder of the chapter proceeds as follows. Section 3.2 describes the data and the main variables. Section 3.3 exposes the empirical design while results are reported in section 3.4. Finally, section 3.5 concludes.

3.2 Data

My main dataset is derived from Crunchbase (CB)⁸, an online platform providing comprehensive data on private and public companies. Launched in 2007 to track startups, CB constitutes an interesting source of information to study entrepreneurship. It includes detailed information about companies, people involved in the companies (founders, employees, investors), investment activities, IPOs, and acquisitions. An essential feature of this database for my study is its coverage of companies that did not raise any external financing. As opposed to more frequently used databases, it does not focus on VC-backed companies only but encompasses non-VC-backed firms as well. Thus, it provides a more representative sample of the entrepreneurial population. The second key characteristic of this data is that it enables me to track founders' career and collect information about companies where they worked. It provides important details about job positions, their start and end dates that are critical to study serial entrepreneurs.

To collect and validate data, CB relies on crowd-sourcing, machine learning, and in-house data team contribution. Compared to more established data sources⁹, it seems pretty reliable in terms of coverage and accuracy, especially for start-ups located in the US (Dalle et al., 2017, Retterath and Braun, 2020). In addition, along with Pitchbook, CB is the dataset with the highest average coverage for founder information (Retterath and Braun, 2020). It represents the primary data source of a growing number of academic studies (Dalle et al., 2017).

⁸Crunchbase provided me with research access to export data.

⁹Pitchbook, VentureXpert, Venture Source, AngelList and OECD Entrepreneurship Financing Database among other benchmark data.

3.2.1 Sample selection

As of April 2022 ¹⁰, the database contained information about almost 2 million distinct organizations worldwide. I restrict my main analysis to companies located in the US (38% of the initial sample) and for which I am able to identify at least one founder. While I use the entire company-level data to identify career-related variables, the main sample focuses only on companies founded between 2004 and 2017. For companies with missing founding dates but available founder information, I consider the founder's start date as the company's founding date. The starting year of the sample ensures that the coverage of CB is good and accurate enough ¹¹. The upper bound of the founding year ensures enough time to observe the startup's outcome by April 2022. After removing observations with date incoherence - such as those for which the outcome date or the first financing date precedes the founding date - and eliminating companies for which the exit date is anterior to the first financing date (if any), I end up with a sample of 98 004 distinct companies and 135 523 founders. However, as the primary focus of this study is serial entrepreneurs, I further restrict my sample in two respects. First, I only include observations of founders for whom career information is available. If a founder appears in the people data of Crunchbase only once, with the focal company, she is not included in the sample. Indeed, as Crunchbase continuously collects and completes the data, it is unclear whether the information is missing or whether the founder does not have any other experience. Hence, the main sample is more likely to include founders who worked in more than one company. Second, in most of the analysis I compare first-time entrepreneurs to second-time entrepreneurs who started their second venture after the exit of the first one. For robustness analyses, I also use an extended sample including serial founders with multiple past ventures. Hence, the final sample contains observations for 40 235 distinct companies founded between 2004 and 2017 as well as 50 336 founders.

¹⁰Date of the last export of the data.

¹¹Ferrati and Muffatto (2020) suggests that although the record of creation dates was low until 2013, the investment round level data offers a good coverage after 2001. I chose 2004 as the sample's start based on the number of US companies founded each year.

3.2.2 Main variables

Founder information. I collect founder information from the people data of CB after identifying founders through their job titles. I consider as founders not only those for whom the job titles directly contain words such as “founder” or “owner”, but also CEOs who started their position at the company’s founding date but whose job titles do not define them as founders. Some investors are also reported as founders after joining the board of the companies, I ensure that they are not considered as such in my analysis. In the final sample, the average size of the founding team is 2.1.

The people data from CB enables me to build variables on gender, education, and career-related information. Regarding education, I identify *Ph.D.*, *Master*, *Master (non-MBA)*, *MBA*, *Bachelor* as well as *STEM* degrees (any kind) thanks to available degree types and subjects. To take into consideration the level of education in the regressions through fixed effects, I additionally built a *Highest Degree* variable that reports the highest degree obtained by a person, if any¹². In the main set of regressions, I include education variables referring to degrees completed before the founding date of a company¹³. As institution names are also available, I identified founders who attended *Elite Schools* following Gompers and Xuan (2016) and Amornsiripanitch et al. (2022)¹⁴. Regarding founders’ careers, I determine both the past and future experiences of the founders with respect to the focal observation.

As I focus on serial entrepreneurs, the main variables are related to founder experiences. *Founder Before* is a dummy variable indicating whether the founder is identified as the founder of any other company founded before the focal firm, while *Founder Again* reveals whether the founder appears as the founder of any other company after the outcome date of the focal venture. While *Founder Before* refers to all serial entrepreneurs, *Second-time E* corresponds to those who had only one venture before the focal one. I separately included information relative to the founders’ first experience (first job position) and their position right after the outcome date of the focal firm (next position). As I do not have information about the founders’ age, I computed the time from their first job to balance this and to take into account more precisely their active work experience¹⁵.

¹²By highest degree I consider the following order: PhD > Master > Bachelor.

¹³However, due to a high number of missing completion dates, this reduces the sample size.

¹⁴Elite universities include: Brown University, Columbia University, Cornell University, Dartmouth College, Duke University, Harvard University, Massachusetts Institute of Technology, Northwestern University, Princeton University, Stanford University, University of California, Berkeley, University of Chicago, University of Pennsylvania and Yale University.

¹⁵I do not use the time since their graduation due to missing completion dates.

One last important set of variables concerns the general managerial ability of founders. Following Custódio et al. (2013), I use the number of different firms, positions, industries in which the founder worked, as well as the dummy variable *Founder Before*, to identify the *General Ability Index* of founders at the time of their first venture and when they start the focal venture. I also use *General Ability Index 2*, that excludes the variable *Founder Before* from the principal component analysis¹⁶.

Company information. Company-related variables that are constructed based on directly available information are: location dummies for CA, NY and MA, industry variables (see Appendix 3.7.1 for details) and dummies for broad categories such as “*Biotechnology*”, “*Internet/Computer*”, “*Medical/Health*”, “*Financial Services*”, financing characteristics and exit date. The exit date corresponds to the first event date between an IPO, an acquisition and a closure. When closure dates are missing for operating companies defined as failed, I consider the exit date as 3 years after the last funding of the firm.

Outcome variables. Outcome variables are defined with respect to exit events. Although the data include non-VC-backed founders who do not necessarily have same perceptions of successes and failures, since I mainly study VC investors and VC financing, I decided to rely on the most common definitions of success and failure used in the VC literature. Thus, a successful exit is defined as an exit through an IPO or an acquisition and is captured by the dummy *Successful Exit*. Regarding the dummy variable *Failure*, I rely on two definitions, a broad and a narrow one. The narrow definition of failure considers a company as failed if it closed without achieving a successful exit. The broad definition additionally includes firms that are operating and received any VC or angel financing but did not obtain further financing since more than 3 years. The broad definition is the one used in the main regressions while robustness tests are ran with the narrow definition. In unreported results, I extended this definition to low value acquisitions: those for which the acquisition price is lower than the total funding, or lower than 25M/50M. I also built past outcome related dummies such as *Failure Before* and *Success Before* for the first venture of serial entrepreneurs and *Any Failure Before* as well as *Any Success Before* for any of their past ventures.

¹⁶see Custódio et al. (2013) and Custódio et al. (2017) for more details about the index. Although this measure is used for CEOs, its definition is well-suited for founders as well, in line with Lazear (2005).

3.2.3 Descriptive statistics

Table 1 presents descriptive statistics at founder and company level. It compares first-time entrepreneurs to second-time entrepreneurs. These latter represent 6.3% of the sample¹⁷. Overall, first-time entrepreneurs appear to be less educated than serial founders. They are also more likely to start their career as founders or CEOs but less likely to hold VP or other C-level positions. As they seem to have shorter careers on average, they are also less generalists than second-timers. However, compared to when these last ones started their first venture, new entrants are more generalist. Regarding company characteristics, serial founders are on average more likely to start in California within internet/computer related sectors. As far as the financing characteristics of their companies are concerned, not only new entrants are, on average, 16% less likely to raise VC financing but they also receive smaller total funding amounts. Lastly, outcome-related summary statistics suggest that new entrants have lower chances to succeed while they fail more frequently on average. Table A7 of the Appendix provides the same statistics within serial entrepreneurs who experienced past VC financing and those who did not.

3.3 Empirical Strategy

In order to shed more light on the perception of failure, I first explore whether failure might be a barrier to start a new venture again. I track founders' future career and identify whether they are founders of other companies either in their next job position or at any other time in the future.

Then, I compare failed entrepreneurs to successful ones following the empirical specification below:

$$Founder\ Again_{jf} = \beta Failure_{jf} + \theta' X_{jf} + \alpha_i + \gamma_s + \eta_t + \epsilon_{jf} \quad (3.1)$$

The dependent variable is a dummy variable that is equal to one if the founder j starts a new venture in the future, and zero otherwise. The main independent variable, $Failure_{jf}$, is a dummy that equals one if the founder experience failure in the focal venture f . The vector of controls X_{jf} includes controls for founder and venture characteristics such as gender, the time since the first job of the founder, the number of companies founded before, the existence of any experience outside of the US, the company's age at exit and an education dummy for attendance of top US schools.

¹⁷Serial founders who sequentially started their venture (excluding portfolio entrepreneurs) represent 10% of the sample when they are included.

See Appendix table 14 for variables descriptions. This main specification also includes fixed effects with respect to the focal venture's characteristics such as industry (α_i), state (γ_s) and exit year (η_t).

To further understand how important past founder experience and outcomes are for raising VC funds, I compare second-time entrepreneurs to first-time entrepreneurs. Under the hypothesis that VCs have a positive perception of past experience, I should observe a significant funding gap between serial entrepreneurs and new entrants. If such a difference exists, then, to further clarify whether VCs perceive experience as important on its own or whether the gap is driven by successful experiences only, I repeat the comparison based on past outcomes. While successful experiences are expected to be rewarded, under the experimentation culture hypothesis, past failures should not be penalized. To compare the likelihood of obtaining VC financing for new entrants and serial founders, I use the following empirical specification:

$$VCFinancing_j = \beta F_j + \theta' X_j + \alpha_i + \gamma_s + \eta_t + \epsilon_j \quad (3.2)$$

The dependent variable is a dummy variable that is equal to one if the focal venture of founder i raises VC financing, and zero otherwise. The main independent variable, F_j represents the founder's category concerning past experience or past outcome. Thus, it is either the dummy variable *Second-time E* or dummy variables *Failure Before/Success Before*. *Second-time E* equals one if the founder is a second-time entrepreneur and zero if she is a first-timer. *Failure Before* takes the value of one if the first venture of the founder closed without achieving a successful exit or if it received its last VC financing more than 3 years ago. *Success Before* takes the value of one if the first venture of the founder exited through an IPO or an M&A. In specification where the main independent variable accounts for the past outcome, to keep first-time entrepreneurs as the reference group, I restrict the sample accordingly by excluding serial founders who experienced success (failure) rather than failure (success) in their past venture. Therefore, *Failure Before* and *Success Before* take the value of zero if the founder is a first-timer. The vector of controls X includes controls of founder characteristics such as gender, the time since the first job of the founder, the general ability index of the founder and education dummy variables including degrees hold and attendance of top US schools. This main specification also includes fixed effects with respect to the focal venture's characteristics such as industry (α_i), state (γ_s) and founding year (η_t).

Lastly, to justify reasons behind the eventual differences in VC fundraising, I compare outcomes following the specification below:

$$Outcome_{jf} = \beta_1 F_j + \beta_2 VC \text{ Financing} + \theta' X_j + \alpha_i + \gamma_s + \eta_t + \epsilon_{jf} \quad (3.3)$$

$Outcome_{jf}$ corresponds to the outcome of venture f founded by entrepreneur j . It is either the dummy variable *Successful Exit* or the dummy variable *Failure*. F_j represents the founder's category concerning past experience or past outcome. Thus, it is either the dummy variable *Second-time E* or dummy variables *Failure Before/Success Before*. *VC Financing* is a dummy variable that takes the value of one if venture f received VC financing. Control variables are restricted to gender, the time since the first job of the founder, and top US school attendance. Indeed, *VC Financing* already captures most of the founder's education or experience-related characteristics. Fixed effects are similar to those defined in previous equations.

3.4 Main Results

While in Europe, the existence of a negative perception of failure that prevents entrepreneurs from accessing finance and creating new firms is already documented (Cahn et al., 2021), there is only anecdotal evidence about the perception of failure in the US. These latter suggest that failure is not stigmatized and is even considered as a stepping stone to success. However, most of these anecdotes concern successful serial founders from the Silicon Valley and probably overlook an important fraction of entrepreneurs who experienced failure. Therefore, it is important to understand whether experience actually matters more than outcome in the US or if failure constitutes a barrier to reentering the entrepreneurial market and obtaining financing even there.

3.4.1 Failure experience and the decision to start again

In this subsection, I focus on the relationship between failure and reentry in the entrepreneurial market. Under the assumption that, in the US, there exists an experimentation culture that positively values failure, there should not be a significant difference in the likelihood of starting a new venture for entrepreneurs who experienced failure and those who experienced success. To test this hypothesis, I track founders' career and identify whether they started a new business after the exit date of the focal start-up. I look both at their entire future career (*Founder Again*) and

at the first job position reported after the exit of the focal firm (*Founder Again Next*). To ensure that founders have enough time to start a new job, the sample excludes observations for which the exit date is after 2020. Since the remainder of the chapter concentrates on VC financing, to keep coherence, I rely on a common definition of failure that is especially appealing to investors. I consider a firm as failed if, it closes without achieving a successful exit through an IPO or an M&A. I additionally define a firm as failed if it received any VC or angel financing and is reported as operating while the last funding was more than 3 years ago¹⁸.

The results reported in table 2 support the existence of a significant difference in the likelihood to start a new venture between failed and successful entrepreneurs. Founders who experienced failure are on average 16 to 35 % less likely to be founder again compared to those who experienced success. The probability to launch a new business for their next activity is also 13 to 30% lower compared to successful entrepreneurs. The difference is the strongest when comparing entrepreneurs within the same industry and state but across different exit years (columns (1) and (5)). Although adding *Exit Year* fixed effects in columns (2) and (6) reduces the gap, it remains significant and substantial. All the specifications include controls related to founders' work experience such as the past founder experience, the time since their first job and any work experience outside of the US. In the absence of direct information about the ethnicity or citizenship of founders, the last control helps to indirectly capture eventual cultural differences. To ensure even more comparability between founders, their educational background is also taken into consideration with an *Elite School* control and *Highest Degree* fixed effects in columns (3) and (7). The results are quite similar with this final specification.

To further understand whether this finding is related to the perception of failure, I compare failures that occurred during recession periods to those that happened outside of recessions. Since recession time failures are more likely to be attributed to bad luck, I expect such failures to be less perceived as barriers to start again. Columns (4) and (8) of table 2 support this prediction. While exiting during recession times does not matter for successful entrepreneurs to start again, it increases the likelihood of creating a new venture for failed entrepreneurs.

In table 3, I additionally investigate whether, conditional on founding a new firm after the exit date (when the next activity refers to a founder position), entrepreneurs who experienced failure

¹⁸Since the analysis related to this subsection requires to consider the exit year in the regressions, the definition of failure will be restricted to closure without successful exit. All of the results are robust to using the extended definition including active firms for which the exit year is defined as 3 years after the last funding.

are more inclined to change their location compared to successful founders. While it is difficult to test whether such a change is due to an eventual stigmatization of failure, it would reinforce the idea that failure is negatively perceived even in the US. Columns (1) and (2) report the results for whether the next venture's location is outside of the US. State level changes within the US are exposed in columns (3) and (4). The overall findings from this table suggest that entrepreneurs are more prone to start their new venture in a new place when they experienced failure. Compared to successful founders, they are 4.6 percentage points more likely to start their next firm outside of the US, and 4.8 percentage points more likely to start in another state conditionally on staying in the US. Column (2) includes an interaction term to ensure that failed founders do not leave the US due to a potential attachment to other countries (this is captured by their past work experience outside of the US). Founders' past experience outside the US does not seem to explain their incentive to start again outside since the coefficient of the *Failure* variable remains significant. To verify whether similar results are obtained conditional on receiving VC financing in the next venture, I replicate the analysis in a restricted sample and report the results in column (4). Failed entrepreneurs who received VC financing are even more likely to have a new venture located in a different place compared to the previous one. This is consistent with the search of capital in new locations to avoid an eventual stigmatization of failure from investors.

Although the findings from this subsection are in line with the existence of a negative perception of failure, they do not provide causal evidence of such a perception. Alternative explanations related to founders' loss of confidence or preference for outside options are not excluded. Nevertheless, further investigation of serial founders' access to finance might be helpful to complement this first suggestive evidence.

3.4.2 Founder experience and access to VC Financing

While the previous subsection provides a comparison of successful and unsuccessful entrepreneurs, comparing first-time entrepreneurs to serial entrepreneurs who already have a founder experience, would be more insightful to clarify the perception of past entrepreneurial experience. If failure is regarded as a positive experience, failed entrepreneurs should not be at a disadvantage compared to new entrants in their search of financing. On the contrary, their past experience should facilitate access to finance relatively to first-time entrepreneurs. Since VC financing is abundant in tech hubs where failure is even more supposed to be encouraging, and due to the comprehensiveness of CB

data regarding VC financing, I will concentrate on access to VC financing. With such a focus, any support of a negative perception of failure would be underestimated while evidence of a positive perception of experience would be overestimated.

The results reported in this subsection are based on a sample in which serial entrepreneurs correspond to second-time entrepreneurs whose first venture outcome is realized ¹⁹ before the creation of their second venture. This enables me to avoid confounding effects due to multiple experiences²⁰ and ensures that the past outcome is known before any eventual financing of the second venture. By proceeding like this, I also exclude portfolio entrepreneurs who run multiple companies in parallel rather than sequentially.

Analyzing the likelihood of being VC-backed, in table 4, reveals that past experience substantially matters for VC fundraising. With respect to a new entrant within the same industry, year and state, a second-time entrepreneur is on average 21% more likely to use VC financing (columns (1)). The *Time from first job* control additionally shows that the overall work experience is also important to raise VC financing. Following Custódio et al. (2013), I control for the general managerial ability of the founder through the *General Ability Index (GAI)*, adjusted for comparisons between first-timers and serial founders (*GAI 2*²¹). The results show that the index is positively correlated with the probability to have VC financing, suggesting that general managerial abilities increase the likelihood to contract with VC investors. Unsurprisingly, the effect is reduced when adding educational controls in column (2). Along with *Highest Degree* fixed effects and *Elite School* control, to ensure more comparability between first-timers and serial founders, I introduce dummy variables for whether the founder has completed an MBA degree or holds any STEM degree. Both characteristics are at play for access to VC financing. With similar specifications, columns (3) and (4) show that there is no significant difference in VC fundraising between new-entrants and serial founders who experienced failure in their first business. This result suggests that failed entrepreneurs are not stigmatized with respect to similar new entrants. However, it does not support the idea that experience matters more than outcome. Columns (5) and (6) further establish that what is actually important is a successful experience. Such an experience makes founders on average 27% percent more likely to rely on VC financing relative to first-timers. As shown in table

¹⁹A realized outcome refers to a failure or a successful exit, any other outcome that is not defined as success or failure is excluded.

²⁰The appendix exposes robustness tables from a sample including serial founders who started more than one firm (with known outcomes) before the focal venture.

²¹*GAI 2* does not include the variable *Founder Before* in the PCA analysis.

A2, the results are robust to including all serial founders with realized past outcomes.

While these findings document neither a negative nor a positive perception of failure, tables 5 and 6 indicate that what actually matters is past VC experience. Unconditional of the first venture outcome, a second-time founder who has already received VC financing in the first firm is more likely to raise VC financing again compared to a new entrant. On the contrary, for second-time E who were never VC-backed, past experience does not increase the probability of using VC financing. Table 5 shows that the results obtained in table 4 are primarily driven by serial founders with a past VC experience. Columns (1) and (2) document the absence of a funding gap between serial founders who did not raise VC financing before and first-time entrepreneurs. Columns (3) and (4) reveal the existence of a significant difference in VC fundraising between first-timers and second-timers when the latter benefited from VC financing before. In table 6, I further analyse the role played by past outcomes in both cases. The first two columns of the table complement the ones from the previous table. They show that founders without past VC experience but with past failure experience are 6 percentage points less likely to be VC-backed compared to new entrants. Interestingly, those with a successful experience are not favored compared to new entrants. The last two columns confirm that, whether they failed or succeeded, previously VC-backed serial founders are more likely to be VC-backed in their second venture compared to new entrants. Tables A3 and A4 confirm these findings with a sample extended to serial founders with multiple venture experience.

Thus, this subsection establishes that common priors about the experimentation culture and the absence of stigma of failure in the US are not unjustified. However, it shows that they are only true for a specific category of entrepreneurs: those who have already entered the VC circle. Entrepreneurs who never benefited from VC financing might still be stigmatized for their past failure while they are not rewarded for their success. To understand why such a gap exists and whether in both cases the decisions are justified, I analyze the performance and the differences between serial founders with past VC experience and those without.

3.4.3 Past Experience and Future Performance

Why would VC investors favor entrepreneurs who were previously backed by VCs and value their experience more than those of other serial entrepreneurs? Is not it better off for them to expand their horizons and give a chance to non-VC-backed founders as well? To answer these questions, in this subsection, I focus on the performance of the focal ventures considering their founders' past entrepreneurial and VC financing experience. I first study whether and how past founder experience contributes to future performance. We already know from Gompers et al. (2010) that serial founders outperform new entrants and that success breeds success. However, their analysis being restricted to a sample of VC-backed companies, I test whether their results find support in a more general setting. I then concentrate on past VC experience and try to shed light on the determinants of VCs' eventual preference for previously backed serial founders.

Founder experience and performance

My first set of results is in line with Gompers et al. (2010) and support that past outcome is a key determinant in the contribution of experience to future performance. Therefore, it seems that what matters is not the experience itself but the entrepreneurial skill. However, I do not find that failed entrepreneurs underperform new entrants. Hence, there is no apparent performance-related reason to prefer first-timers over failed entrepreneurs, nor a reason to prefer the latter over the former. If such preferences exist, then it means that failure is stigmatized or past experience is overestimated.

Table 7 shows that past experience matters for future success but does not help to avoid failure. Indeed, columns (1) and (2) suggest that a second-time E is, on average, 13.7 to 16% more likely to exit successfully with respect to a comparable new entrant. Regarding the likelihood of failure, columns (4) and (5) do not display a significant difference between first-timers and second-timers. In tables 8 and 9, I dig further within past experience by analyzing how past outcomes affect performance. Table 8 focuses on failure experience. It shows that past failure neither significantly decreases the likelihood of success (columns (1) to (3)) nor increases the probability of failure (columns (4) to (6)). Thus, I do not find evidence that serial founders who experienced failure before perform worse than new entrants. This result supports that stigmatizing entrepreneurial failure is not justified from the performance perspective. As far as past successful founders are concerned, table 9 encourages rewarding past success. Consistent with Gompers et al. (2010),

columns (1) to (3) show that successful entrepreneurs are more likely to succeed again. Although in column (4), the coefficient of *Success Before* is positive and significant at 10% , suggesting that successful entrepreneurs are also less likely to fail, this result is not robust to comparing entrepreneurs with the same education level in column (5).

To further understand whether VC financing might help serial founders to achieve success or to escape failure, I introduce the interaction term *Second-time E × VC Financing* in columns (3) and (6) of previous tables. While VCs do not seem to contribute to the success of serial entrepreneurs (column (3)), they appear to help them to avoid failure (column (6)). This result holds for both entrepreneurs who experienced past failure and those who were previously successful. It is interesting to also notice that VC financing increases not only the likelihood of success but also the probability of failure for new entrants. This finding supports that VCs push new entrants to fail fast while they help serial founders to delay failure. Hence, VC financing remains attractive overall for serial founders to increase the likelihood of survival, no matter their past outcomes.

Past VC experience and performance

Now that I exposed the general results related to past entrepreneurial experience and performance, I explore whether these findings hold for all serial founders or if there are differences between those who benefited from VC financing in their first venture and those who did not. Indeed, subsection 3.4.2 revealed that VCs push the experimentation culture, without stigmatizing failure, within a specific group of serial founders: those who were backed by VCs in their first venture. A reasonable explanation of this finding is that the two groups are different and: (1) either past experience is more valuable within the group that experienced VC financing in the past, (2) or VCs have other reasons to believe that previously VC-backed entrepreneurs will outperform other serial entrepreneurs.

Table 10 compares serial founders with past VC experience to those without. Panel A shows that the previous results with respect to success are mainly due to serial founders who did not experience VC in their first venture. In columns (4) to (6), the coefficients of the variable *Second-time E* are not only larger compared to columns (1) to (3), but also always significant. Thus, previously VC-backed founders do not outperform non-VC-backed serial entrepreneurs. In addition, results suggesting that they do better than new entrants are weak. Panel B replicates the same analysis for failure and does not highlight a significant difference between these two types of serial founder.

Moreover, table 11 confirms this finding when looking at past outcomes. It shows that, while there is no difference between the two groups conditional on past failures, among the successful serial founders, only those who did not receive VC financing before perform significantly better than new entrants.

VCs may have two plausible reasons to believe that entrepreneurs with past VC experience would outperform other serial founders. First, they might believe that they add value not only to startups but also to founders. Thus, they could think that founders learn from them unconditional on the outcome. In the specific case of failed entrepreneurs, VCs may help them to notice their mistakes and learn from their errors. Therefore, VCs would trust previously backed entrepreneurs more in their ability to learn from their failure. My results reject this value adding theory of VCs as past experience is not more valuable for previously VC-backed founders.

Secondly, as VCs go through a selection process, these founders might originally have the profile of “*the successful entrepreneur*” defined by VCs. In this case, prior VC experience plays a signaling or a certification role. Thus, VCs may rely on it to screen serial founders. This screening theory could make sense if founders with VC experience are on average different from other serial founders. Then, conditional on being VC-backed we should not observe much differences between the two groups, neither in terms of observable characteristics, nor in terms of performance.

Table A7 presents the means and differences between founders with and without prior VC experience for a variety of biographical characteristics. It underlines that the main differences are related to founders’ education and past job experience ,i.e., characteristics that are arguably at play both for VC financing and future success. Second-timers who did not receive VC financing in their first venture are on average less likely to hold PhD, MBA or any STEM degree. They are also less likely to be from top US universities. Regarding their first job experience, they are less likely to start their career as entrepreneurs, VPs or non CEO C-levels. Besides, previously VC-backed founders are more generalist profiles on average. They have worked in a larger number of distinct firms and industries under different positions. In addition, they were already more generalist before starting their first venture. Table 12 further exposes these differences in a multivariate framework, comparing serial founders who started the same year, within the same state and industry. It confirms that in the initial sample, there are significant differences between the two groups of serial founders in terms of educational background, first job positions and general managerial ability (columns (1) to (6)). It also shows that most of the differences disappear conditional on

being backed by VCs in the focal venture (columns (7) to (12)). Remaining differences essentially concern the first job position of the founder.

As established in table A8, all these characteristics play an important role for future performance. Therefore, knowing that VCs themselves did not add value to founders, there should not be any difference in performance, between the two groups, after the screening. Table 13 confirms this prediction and additionally suggest that previously VC-backed founders are more likely to obtain financing from more failure tolerant VCs²² in first hand. This further contributes to explaining why in addition to past successes, prior failures are also rewarded in this group. It also raises questions for future research about the self-selection of these founders towards investors known as more failure tolerant. My on going research at VC investor level aims to shed more light on investor-related channels.

Overall, all these findings suggest that there might be interesting opportunities among serial founders who never entered the VC circle. By reducing the differences between the profiles VCs select, they also decrease their chance to discover other characteristics of serial founders that might be essential for success. In addition, the previous results support that VCs do not add value to serial founders while they help them to avoid failure. Given that Crunchbase mainly tracks tech companies that seek financing, and has better coverage of companies that received at least one type of financing, my results should not be driven by the fact that serial founders without past VC experience are less prone to request VC financing. Such cases should be limited and probably already excluded from my main sample due to missing information. Nevertheless, I still ensure that the existence of alternative sources of financing do not reduce their likelihood of raising VC financing. I exclude this alternative explanation by running a robustness test where I control for other financing sources such as angel financing, debt financing, and crowdfunding (see table A5). Despite this, if my results are explained by such founders' reduced incentive to ask for VC financing, they still hold important implications for them. Indeed, in this case, serial founders who escape VC financing might miss opportunities to grow and survive longer. If I do not find that VCs add value to serial founders, I notice that they help them to avoid failure. Thus, if such founders aim to remain operating without necessarily achieving a successful exit, they might benefit from VC financing. If their goal is to go public or get acquired, then, paradoxically, they are already performing well without VCs' support.

²²Following Tian and Wang (2014), *Failure Tolerance* is computed based on the average investment duration of past failed projects while *Failure Tolerance 2* relies on the number of rounds.

3.5 Conclusion

Experimentation in entrepreneurship supposes failing and trying again. While the US is considered as a place where an experimentation culture exists, there is little empirical evidence to support this. This chapter analyzes how past experience is actually perceived in the US and how VC investors contribute to experimentation. Using comprehensive data on serial entrepreneurs, I first examine whether failure might be a barrier to starting a new venture again. Then, I study whether VC financing is conditioned by past outcomes and whether this has implications in terms of performance.

After observing that founders who experienced failure are, on average, less likely to start again when compared to successful founders, I also noticed that conditional on starting again, failed entrepreneurs are more prone to start elsewhere. Therefore, questioning the perception of failure, in the US, seems justified. To clarify these observations, I focus on serial entrepreneurship and VC fundraising. When comparing second-time entrepreneurs to first-time founders, I find that failure is neither stigmatized nor rewarded, while success increases the likelihood of getting VC financing. However, a further look at a specific category of serial founders reveals significant differences. It shows that the findings in favor of an experimentation culture are mainly driven by one of them. I find that serial entrepreneurs who benefited from VC financing in their first venture are more likely to raise VC financing and to benefit from the experimentation culture. Those who never experienced VC financing, are stigmatized if they failed in the past and not necessarily rewarded if they succeeded.

Such a difference can make sense if founders with past VC experience perform better than those who never received VC financing. Indeed, as VCs contribute to startups in many aspects (Hellmann and Puri, 2002, Hsu, 2006, Sørensen, 2007, Bottazzi et al., 2008, Chemmanur et al., 2011, Bernstein et al., 2016, Ewens and Marx, 2018), we can also imagine that they add value to founders as well. VCs can help entrepreneurs to notice their errors and help them to learn from their mistakes. In that case, VCs have relevant reasons to believe that such founders have more potential to learn from failure. Nevertheless, my results suggest that VCs do not add such value and previously backed serial founders do not perform better than other serial entrepreneurs.

Another explanation concerns VCs' selection process. As VCs carefully screen entrepreneurs, they might rely on past selections that play a certification role for them. In this case, we should not observe much difference between VC-backed founders with past VC experience and those

without. My results confirm that existing differences in the characteristics of founders disappear when the sample is conditioned to VC-backed startups. Thus, relying on some predefined selection criteria might prevent from discovering other criteria more specific to serial founders. Overall, there might be interesting investment opportunities among founders who have never benefited from VC financing before.

3.6 Figures and Tables

Table 1: First and second-time entrepreneurs' characteristics

The table presents characteristics differences between first-time and second-time entrepreneurs. Panel A compares founders' educational background, panel B focuses on their career and panel C provides the focal venture's characteristics. The mean and number of observations are reported for each of group as well as differences in means and their t-stat.

	All		New entrants		Second-timers		difference	t-stat
	N	Mean	N	Mean	N	Mean		
Panel A. Founder characteristics								
Female	52,795	0.115	49,495	0.119	3,300	0.057	0.0626***	(10.91)
PhD	31,482	0.053	29,273	0.052	2,209	0.063	-0.0106*	(-2.14)
MBA	31,482	0.097	29,273	0.096	2,209	0.110	-0.0142*	(-2.17)
Master (non MBA)	31,482	0.115	29,273	0.114	2,209	0.134	0.0199**	(-2.83)
Bachelor	31,482	0.505	29,273	0.502	2,209	0.545	-0.0427***	(-3.87)
STEM	31,482	0.273	29,273	0.269	2,209	0.330	-0.0613***	(-6.24)
Elite School	31,482	0.304	29,273	0.298	2,209	0.388	-0.0893***	(-8.81)
Panel B. Founder Career								
First Experience								
First experience_founder	52,795	0.648	49,495	0.642	3,300	0.529	0.113***	(-11.18)
First experience_VP	52,795	0.056	49,495	0.056	3,300	0.738	-0.682***	(-0.65)
First experience_C level	52,795	0.139	49,495	0.139	3,300	0.058	-0.081***	(-0.21)
First experience_CEO	52,795	0.251	49,495	0.250	3,300	0.140	0.11***	(-2.28)
Time from first experience (years)	52,795	3.143	49,495	2.655	3,300	10.456	-7.801***	(-80.32)
Overall experience before the focal firm								
Different firms	52,795	0.771	49,495	0.681	3,300	2.114	-1.433***	(-59.59)
Different positions	52,795	0.855	49,495	0.774	3,300	2.066	-1.292***	(-53.22)
Different industry	52,795	0.498	49,495	0.452	3,300	1.179	-0.726***	(-50.21)
Different industry (founded)	52,795	0.063	49,495	0.023	3,300	0.668	-0.646***	(-189.34)
GAI (general ability index)	52,795	-0.542	49,495	-0.667	3,300	1.327	-1.994***	(-91.65)
Overall experience before the first venture								
Different firms	52,795	0.669	49,495	0.681	3,300	0.492	0.189***	(8.14)
Different positions	52,795	0.761	49,495	0.774	3,300	0.558	0.216***	(9.19)
Different industry	52,795	0.443	49,495	0.452	3,300	0.310	0.142***	(10.08)
GAI (general ability index)	52,795	0.822	49,495	0.847	3,300	0.437	0.411***	(9.61)
Panel C. Startup characteristics								
Geography								
Company located in CA	52,795	0.396	49,495	0.390	3,300	0.487	-0.0963***	(-10.96)
Company located in NY	52,795	0.142	49,495	0.143	3,300	0.140	0.00288	(0.46)
Company located in MA	52,795	0.061	49,495	0.060	3,300	0.067	-0.00689	(-1.60)
Industry								
Internet/Computer	52,795	0.625	49,495	0.622	3,300	0.657	-0.0348***	(-4.00)
Biotechnology	52,795	0.030	49,495	0.030	3,300	0.027	0.00331	(1.08)
Medical/Health	52,795	0.079	49,495	0.079	3,300	0.080	-0.00111	(-0.23)
Financial Services	52,795	0.074	49,495	0.075	3,300	0.067	0.00792	(1.68)
Financing								
VC financing	52,795	0.396	49,495	0.386	3,300	0.544	-0.158***	(-18.01)
Angel Financing	52,795	0.240	49,495	0.236	3,300	0.302	-0.0659***	(-8.59)
Crowdfunding	52,795	0.066	49,495	0.066	3,300	0.062	0.00432	(0.97)
Debt Financing	52,795	0.013	49,495	0.013	3,300	0.010	0.00236	(1.18)
First financing amount	18,934	5.824	17,439	5.750	1,495	6.692	-0.942	(-0.76)
First vc financing amount	16,375	6.171	14,954	6.076	1,421	7.168	-1.092	(-1.18)
Total funding	29,053	48.941	26,966	47.485	2,087	67.750	-20.27**	(-3.00)
Nb of rounds	33,392	3.108	31,019	3.089	2,373	3.354	-0.265***	(-4.90)
VC Failure tolerance	20,092	0.666	18,341	0.664	1,751	0.690	-0.0266	(-1.47)
VC Failure tolerance 2	20,092	1.315	18,341	1.314	1,751	1.330	-0.0168	(-1.20)
Time between first to second round	21,702	1.290	20,037	1.290	1,665	1.285	0.00500	(0.17)
Outcome								
Successful Exit	52,795	0.218	49,495	0.216	3,300	0.260	-0.0445***	(-5.99)
Exit_IPO	52,795	0.021	49,495	0.020	3,300	0.031	-0.0101***	(-3.92)
Exit_Acq	52,795	0.197	49,495	0.195	3,300	0.229	-0.0344***	(-4.80)
Failure	52,795	0.148	49,495	0.149	3,300	0.131	0.0182**	(2.85)
Failure_Operating	48,722	0.317	45,581	0.318	3,141	0.289	0.0294***	(3.43)

Table 2: Starting Again After a Failure Experience

The table reports the results of a linear probability model where the dependent variable is a dummy variable equal to one if the founder starts a new business after the focal venture. *Founder Again* indicates whether the founder starts a new venture at any time after the exit of the focal one while *Founder Again Next* is restricted to the first job position after the exit. *Failure* is a dummy variable that takes the value of one if the firm closes without achieving a successful exit (IPO or M&A) and zero if it succeeds. The variable *Female* indicates whether the founder is a female. *Elite School* is a dummy variable that is equal to one if the founder attended a top US school. *Past Founder Experience* is the log of one plus the number of firms created by the founder before. *Time from first job* corresponds to the log of one plus the time since the first job of the founder. *Non-US Experience* is a dummy variable for whether the founder had any work experience outside of the US. *Company Exit Age* is the age of the company at the exit date in years. Lastly, *Recession Exit* is a dummy variable that takes the value of one if the firm exits during a recession period. The unit of observation is the company-founder pair. Clustered standard errors at the company level are reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5% and 10% level, respectively.

	Founder Again				Founder Again Next			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Failure	-0.092*** (0.009)	-0.044*** (0.008)	-0.042*** (0.008)	-0.094*** (0.009)	-0.056*** (0.008)	-0.025*** (0.008)	-0.025*** (0.007)	-0.059*** (0.008)
Female	-0.057*** (0.012)	-0.036*** (0.012)	-0.036*** (0.012)	-0.057*** (0.012)	-0.040*** (0.011)	-0.027** (0.011)	-0.027** (0.011)	-0.040*** (0.011)
Elite School	0.024*** (0.009)	0.009 (0.008)	0.010 (0.008)	0.024*** (0.009)	0.013 (0.008)	0.003 (0.008)	0.004 (0.007)	0.012 (0.008)
Past Founder Experience	0.060*** (0.012)	0.079*** (0.011)	0.079*** (0.010)	0.061*** (0.012)	0.048*** (0.010)	0.060*** (0.010)	0.060*** (0.010)	0.048*** (0.010)
Time from first job	-0.027*** (0.004)	-0.026*** (0.004)	-0.027*** (0.004)	-0.027*** (0.004)	-0.029*** (0.004)	-0.029*** (0.004)	-0.029*** (0.004)	-0.029*** (0.004)
Non-US Experience	0.025* (0.013)	0.026** (0.012)	0.026** (0.012)	0.025* (0.013)	0.010 (0.011)	0.011 (0.011)	0.012 (0.011)	0.010 (0.011)
Company Exit Age	-0.034*** (0.002)	-0.012*** (0.002)	-0.012*** (0.002)	-0.034*** (0.002)	-0.024*** (0.001)	-0.009*** (0.001)	-0.010*** (0.002)	-0.024*** (0.001)
Recession Exit				0.044 (0.031)				-0.010 (0.026)
Failure × Recession Exit				0.141** (0.065)				0.145** (0.062)
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Exit Year	No	Yes	Yes	No	Yes	Yes	Yes	No
Highest Degree	No	No	Yes	No	No	No	Yes	No
Observations	12,676	12,676	12,676	12,676	12,676	12,676	12,676	12,676
R ²	0.063	0.151	0.152	0.064	0.041	0.088	0.089	0.042

Table 3: Starting Again After a Failure Experience - New Location

The table reports the results of a linear probability model where the dependent variable is: in columns (1) and (2), a dummy variable equal to one if the founder starts a new business outside of the US, and in columns (3) and (4), a dummy variable equal to one if the founder's next venture is in the same state as the focal firm. The sample is restricted to founders identified as founder again in their next job position (after the exit date of the focal firm). In columns (3) and (4), it is further restricted to founders who created their new venture again in the US. Column (4) exposes the results for entrepreneurs who obtained VC financing in their next venture. *Failure* is a dummy variable that takes the value of one if the firm closes without achieving a successful exit (IPO or M&A) or if an operating firm that obtained VC or angel financing did not receive any financing since at least 3 years. *Non-US Experience* is a dummy variable for whether the founder had any work experience outside of the US. The variable *Female* indicates if the founder is a female. *Elite School* is a dummy variable that is equal to one if the founder attended a top US school. In all regressions controls include *Past Founder Experience*, *Time from first job* and *Company Exit Age*. The unit of observation is the company-founder pair. Clustered standard errors at the company level are reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5% and 10% level, respectively.

	Outside US		Within US - Same State	
	(1)	(2)	(3)	(4)
Failure	0.046*** (0.014)	0.048*** (0.013)	-0.048** (0.022)	-0.067** (0.032)
Non-US Experience	0.151*** (0.025)	0.157*** (0.032)	-0.018 (0.033)	-0.008 (0.043)
Female	-0.013 (0.021)	-0.013 (0.021)	-0.029 (0.036)	-0.078 (0.054)
Elite School	-0.036*** (0.013)	-0.036*** (0.013)	-0.013 (0.020)	-0.009 (0.027)
Failure × Non-US Experience		-0.012 (0.049)		
Industry	Yes	Yes	Yes	Yes
State	Yes	Yes	Yes	Yes
Exit Year	Yes	Yes	Yes	Yes
Highest Degree	Yes	Yes	Yes	Yes
Observations	2,495	2,495	2,254	1,203
R ²	0.070	0.070	0.132	0.191

Table 4: VC Financing and Past Experience

The table reports the results of a linear probability model where the dependent variable is a dummy variable equal to one if the company receives VC financing. *Second-time E* is a dummy variable indicating whether the founder is a second-time entrepreneur. *Failure Before* is a dummy variable that takes the value of one if a second-time founder experienced a failure in her first venture. *Success Before* is a dummy for whether the first venture of a second-time entrepreneur went public or was acquired. The variable *Female* indicates whether the founder is a female. *Time from first job* corresponds to the log of one plus the time since the first job of the founder. *GAI 2* refers to the general ability index of the founder. *Elite School* is a dummy variable that is equal to one if the founder attended a top US school. To keep first-timers as the reference group, past successful founders are excluded from the sample in columns (3) and (4), and founders with a failure experience are excluded from the sample in columns (5) and (6). The unit of observation is the company-founder pair. Clustered standard errors at the company level are reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5% and 10% level, respectively.

	VC Financing					
	(1)	(2)	(3)	(4)	(5)	(6)
Second-time E	0.083*** (0.010)	0.084*** (0.012)				
Failure Before			0.008 (0.018)	0.020 (0.022)		
Success Before					0.110*** (0.011)	0.104*** (0.013)
Female	-0.018*** (0.007)	-0.001 (0.008)	-0.019*** (0.007)	-0.003 (0.009)	-0.018*** (0.007)	-0.002 (0.008)
Time from first job	0.016*** (0.003)	0.015*** (0.004)	0.019*** (0.004)	0.018*** (0.004)	0.015*** (0.003)	0.015*** (0.004)
GAI 2	0.011*** (0.002)	0.004* (0.002)	0.009*** (0.002)	0.003 (0.003)	0.012*** (0.002)	0.005** (0.002)
Elite School		0.093*** (0.007)		0.095*** (0.007)		0.091*** (0.007)
MBA		0.026** (0.013)		0.029** (0.013)		0.026** (0.013)
STEM		0.053*** (0.008)		0.053*** (0.008)		0.052*** (0.008)
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Founding Year	Yes	Yes	Yes	Yes	Yes	Yes
State	Yes	Yes	Yes	Yes	Yes	Yes
Highest Degree	No	Yes	No	Yes	No	Yes
Observations	52,802	31,488	50,399	29,817	51,905	30,950
R ²	0.076	0.091	0.070	0.086	0.077	0.092

Table 5: VC Financing and Past VC Experience

The table reports the results of a linear probability model where the dependent variable is a dummy variable equal to one if the company receives VC financing. *Second-time E* is a dummy variable indicating whether the founder is a second-time entrepreneur. The sample is split with respect to the past VC financing experience of second-timers. In columns (1) and (2), the variable *Second-time E* refers to serial entrepreneurs who did not receive any VC financing in their first venture. Columns (3) and (4) report results from the subsample in which all serial founders have experienced VC financing in their first venture. The variable *Female* indicates whether the founder is a female. *Time from first job* corresponds to the log of one plus the time since the first experience of the founder. *GAI 2* refers to the general ability index of the founder. Columns (2) and (4) additionally contains controls for *Elite School*, *MBA* and *STEM* degrees. The unit of observation is the company-founder pair. Clustered standard errors at the company level are reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5% and 10% level, respectively.

	VC Financing			
	No Past VC Exp.		Past VC Exp.	
	(1)	(2)	(3)	(4)
Second-time E	-0.001 (0.014)	0.012 (0.017)	0.155*** (0.013)	0.141*** (0.014)
Female	-0.018*** (0.007)	-0.002 (0.009)	-0.018*** (0.007)	-0.003 (0.008)
Time from first job	0.017*** (0.004)	0.017*** (0.004)	0.018*** (0.004)	0.017*** (0.004)
GAI 2	0.011*** (0.002)	0.004 (0.002)	0.010*** (0.002)	0.004 (0.002)
Industry	Yes	Yes	Yes	Yes
Founding Year	Yes	Yes	Yes	Yes
State	Yes	Yes	Yes	Yes
Highest Degree	No	Yes	No	Yes
Observations	51,056	30,272	51,248	30,495
R ²	0.070	0.086	0.078	0.093

Table 6: VC Financing, Past VC Experience and Past Outcome

The table reports the results of a linear probability model where the dependent variable is a dummy variable equal to one if the company receives VC financing. The sample is split with respect to the past VC financing experience of second-time entrepreneurs. *Failure Before* is a dummy variable that takes the value of one if a second-time founder experienced a failure in her first venture. *Success Before* is a dummy variable for whether the first venture of a second-time entrepreneur went public or was acquired. In columns (1) and (2), *Failure Before* and *Success Before* refer to past outcomes of serial entrepreneurs who did not receive any VC financing in their first venture. Columns (3) and (4) report results from the subsample in which all serial founders have experienced VC financing in their first venture. First-time entrepreneurs are the reference group in all the regressions. Successful second-timers are excluded from the sample in columns (1) and (2), and unsuccessful ones are excluded from the sample in columns (3) and (4). Thus, *Failure Before* and *Success Before* are equal to zero when the founder is a new entrant. The variable *Female* indicates whether the founder is a female. *Time from first job* corresponds to the log of one plus the time since the first experience of the founder. *GAI 2* refers to the general ability index of the founder. The unit of observation is the company-founder pair. Clustered standard errors at the company level are reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5% and 10% level, respectively.

	VC Financing			
	No Past VC Exp.		Past VC Exp.	
	(1)	(2)	(3)	(4)
Failure Before	-0.060** (0.023)		0.082*** (0.025)	
Success Before		0.023 (0.016)		0.178*** (0.014)
Female	-0.018*** (0.007)	-0.018*** (0.007)	-0.019*** (0.007)	-0.018*** (0.007)
Time from first job	0.019*** (0.004)	0.017*** (0.004)	0.019*** (0.004)	0.019*** (0.004)
GAI 2	0.010*** (0.002)	0.011*** (0.002)	0.009*** (0.002)	0.010*** (0.002)
Industry	Yes	Yes	Yes	Yes
Founding Year	Yes	Yes	Yes	Yes
State	Yes	Yes	Yes	Yes
Observations	49,971	50,587	49,930	50,820
R ²	0.070	0.071	0.071	0.078

Table 7: Performance and Past Experience

The table reports the results of a linear probability model where the dependent variable is the outcome of the company. *Successful Exit* is a dummy variable equal to one if the company successfully exited via an IPO or an M&A. *Failure* is a dummy that takes the value one if the company closed without achieving a successful exit or if it received its last VC financing more than 3 years ago. *Second-time E* is a dummy variable indicating whether the founder is a second-time entrepreneur. *VC financing* is a dummy for whether the start-up received a VC financing. The variable *Female* indicates whether the founder is a female. *Time from first job* corresponds to the log of one plus the time since the first experience of the founder. *Elite School* is a dummy variable that is equal to one if the founder attended a top US school. The unit of observation is the company-founder pair. Clustered standard errors at the company level are reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5% and 10% level, respectively.

	Successful Exit			Failure		
	(1)	(2)	(3)	(4)	(5)	(6)
Second-time E	0.030*** (0.009)	0.035*** (0.011)	0.038*** (0.010)	-0.008 (0.010)	-0.006 (0.011)	0.037*** (0.013)
VC Financing	0.217*** (0.005)	0.215*** (0.006)	0.218*** (0.005)	0.146*** (0.006)	0.117*** (0.007)	0.151*** (0.006)
Second-time E × VC Financing			-0.016 (0.016)			-0.079*** (0.018)
Female	-0.054*** (0.005)	-0.062*** (0.006)	-0.054*** (0.005)	0.013* (0.007)	0.038*** (0.009)	0.013* (0.007)
Time from first job	0.002 (0.002)	-0.001 (0.002)	0.002 (0.002)	-0.023*** (0.002)	-0.022*** (0.003)	-0.023*** (0.002)
Elite School		0.020*** (0.006)			-0.009 (0.007)	
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Founding Year	Yes	Yes	Yes	Yes	Yes	Yes
State	Yes	Yes	Yes	Yes	Yes	Yes
Highest Degree	No	Yes	No	No	Yes	No
Observations	52,802	31,488	52,802	48,729	29,095	48,729
R ²	0.127	0.135	0.127	0.054	0.048	0.055

Table 8: Performance and Past Failure Experience

The table reports the results of a linear probability model where the dependent variable is the outcome of the company. *Successful Exit* is a dummy variable equal to one if the company successfully exited via an IPO or an M&A. *Failure* is a dummy that takes the value one if the company closed without achieving a successful exit or if it received its last VC financing more than 3 years ago. *Failure Before* is a dummy variable that takes the value of one if the founder is a second-time founder who experienced failure in her first venture and zero if the founder is a new entrant. *VC financing* is a dummy for whether the start-up received a VC financing. The variable *Female* indicates whether the founder is a female. *Time from first job* corresponds to the log of one plus the time since the first experience of the founder. *Elite School* is a dummy variable that is equal to one if the founder attended a top US school. The unit of observation is the company-founder pair. Clustered standard errors at the company level are reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5% and 10% level, respectively.

	Successful Exit			Failure		
	(1)	(2)	(3)	(4)	(5)	(6)
Failure Before	-0.012 (0.013)	-0.015 (0.017)	0.010 (0.014)	0.022 (0.017)	0.023 (0.022)	0.054** (0.023)
VC Financing	0.217*** (0.005)	0.216*** (0.006)	0.218*** (0.005)	0.149*** (0.006)	0.121*** (0.007)	0.150*** (0.006)
Failure Before × VC Financing			-0.048* (0.027)			-0.067** (0.033)
Female	-0.055*** (0.005)	-0.063*** (0.007)	-0.055*** (0.005)	0.012* (0.007)	0.039*** (0.009)	0.013* (0.007)
Time from first job	0.002 (0.002)	-0.001 (0.002)	0.002 (0.002)	-0.023*** (0.002)	-0.022*** (0.003)	-0.024*** (0.002)
Elite School		0.022*** (0.006)			-0.009 (0.007)	
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Founding Year	Yes	Yes	Yes	Yes	Yes	Yes
State	Yes	Yes	Yes	Yes	Yes	Yes
Highest Degree	No	Yes	No	No	Yes	No
Observations	50,399	29,817	50,399	46,437	27,490	46,437
R ²	0.127	0.135	0.127	0.056	0.050	0.056

Table 9: Performance and Past Successful Experience

The table reports the results of a linear probability model where the dependent variable is the outcome of the company. *Successful Exit* is a dummy variable equal to one if the company successfully exited via an IPO or an M&A. *Failure* is a dummy that takes the value one if the company closed without achieving a successful exit or if it received its last VC financing more than 3 years ago. *Success Before* is a dummy variable equal to one if the founder is a second-time entrepreneur who experienced success in her first venture. *VC financing* is a dummy for whether the start-up received a VC financing. The variable *Female* indicates whether the founder is a female. *Time from first job* corresponds to the log of one plus the time since the first experience of the founder. *Elite School* is a dummy variable that is equal to one if the founder attended a top US school. The unit of observation is the company-founder pair. Clustered standard errors at the company level are reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5% and 10% level, respectively.

	Successful Exit			Failure		
	(1)	(2)	(3)	(4)	(5)	(6)
Success Before	0.045*** (0.010)	0.051*** (0.012)	0.052*** (0.013)	-0.020* (0.011)	-0.016 (0.013)	0.028* (0.015)
VC Financing	0.217*** (0.005)	0.217*** (0.006)	0.218*** (0.005)	0.147*** (0.006)	0.117*** (0.007)	0.150*** (0.006)
Success Before \times VC Financing			-0.012 (0.019)			-0.079*** (0.020)
Female	-0.054*** (0.005)	-0.061*** (0.007)	-0.054*** (0.005)	0.013* (0.007)	0.038*** (0.009)	0.013* (0.007)
Time from first job	0.002 (0.002)	-0.001 (0.002)	0.002 (0.002)	-0.023*** (0.002)	-0.022*** (0.003)	-0.023*** (0.002)
Elite School		0.020*** (0.006)			-0.008 (0.007)	
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Founding Year	Yes	Yes	Yes	Yes	Yes	Yes
State	Yes	Yes	Yes	Yes	Yes	Yes
Highest Degree	No	Yes	No	No	Yes	No
Observations	51,905	30,950	51,905	47,880	28,583	47,880
R ²	0.128	0.136	0.128	0.055	0.049	0.055

Table 10: Performance and Past VC Experience

The table reports the results of a linear probability model where the dependent variable is the outcome of the company. *Successful Exit* is a dummy variable equal to one if the company successfully exited via an IPO or an M&A. *Failure* is a dummy that takes the value one if the company closed without achieving a successful exit or if it received its last VC financing more than 3 years ago. *Second-time E* is a dummy variable indicating whether the founder is a second-time entrepreneur. Panel A reports results where the dependent variable is *Successful Exit* while Panel B reports results where the dependent variable is *Failure*. In both panel, the sample is split with respect to the past VC financing experience of second-time entrepreneurs. In columns (1) to (3), *Second-time E* refers to second-timers who did not receive any VC financing in their first venture. Columns (4) to (6) report results from the subsample in which all serial founders have experienced VC financing in their first venture. *VC financing* is a dummy for whether the start-up received a VC financing. The variable *Female* indicates whether the founder is a female. *Time from first job* corresponds to the log of one plus the time since the first experience of the founder. *Elite School* is a dummy variable that is equal to one if the founder attended a top US school. The unit of observation is the company-founder pair. Clustered standard errors at the company level are reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5% and 10% level, respectively.

Panel A: Successful Exit

	Successful Exit					
	Past VC Exp			No Past VC Exp		
	(1)	(2)	(3)	(4)	(5)	(6)
Second-time E	0.020* (0.011)	0.015 (0.014)	0.018 (0.014)	0.039*** (0.012)	0.058*** (0.015)	0.053*** (0.014)
VC Financing	0.218*** (0.005)	0.217*** (0.006)	0.218*** (0.005)	0.217*** (0.005)	0.216*** (0.006)	0.218*** (0.005)
Second-time E × VC Financing			0.004 (0.021)			-0.031 (0.024)
Female	-0.055*** (0.005)	-0.063*** (0.007)	-0.055*** (0.005)	-0.054*** (0.005)	-0.062*** (0.007)	-0.054*** (0.005)
Time from first job	0.002 (0.002)	-0.001 (0.002)	0.002 (0.002)	0.002 (0.002)	-0.001 (0.002)	0.002 (0.002)
Elite School		0.020*** (0.006)			0.023*** (0.006)	
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Founding Year	Yes	Yes	Yes	Yes	Yes	Yes
State	Yes	Yes	Yes	Yes	Yes	Yes
Highest Degree	No	Yes	No	No	Yes	No
Observations	51,248	30,495	51,248	51,056	30,272	51,056
R ²	0.128	0.136	0.128	0.127	0.135	0.127

Table 10: Performance and Past VC Experience (continued)

Panel B: Failure

	Failure					
	Past VC Exp			No Past VC Exp		
	(1)	(2)	(3)	(4)	(5)	(6)
Second-time E	-0.021* (0.012)	-0.012 (0.015)	0.040** (0.019)	0.007 (0.013)	-0.0002 (0.016)	0.034** (0.017)
VC Financing	0.147*** (0.006)	0.119*** (0.007)	0.150*** (0.006)	0.148*** (0.006)	0.119*** (0.007)	0.150*** (0.006)
Second-time E × VC Financing			-0.093*** (0.024)			-0.058** (0.026)
Female	0.013* (0.007)	0.039*** (0.009)	0.013* (0.007)	0.012* (0.007)	0.038*** (0.009)	0.012* (0.007)
Time from first job	-0.023*** (0.002)	-0.022*** (0.003)	-0.023*** (0.002)	-0.023*** (0.002)	-0.022*** (0.003)	-0.023*** (0.002)
Elite School		-0.007 (0.007)			-0.010 (0.007)	
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Founding Year	Yes	Yes	Yes	Yes	Yes	Yes
State	Yes	Yes	Yes	Yes	Yes	Yes
Highest Degree	No	Yes	No	No	Yes	No
Observations	47,274	28,158	47,274	47,043	27,915	47,043
R ²	0.055	0.049	0.055	0.055	0.049	0.055

Table 11: Performance, Past VC Experience and Past Outcomes

The table reports the results of a linear probability model where the dependent variable is *Successful Exit*, a dummy variable equal to one if the company successfully exited via an IPO or an M&A. *Failure Before* is a dummy variable that takes the value of one if the founder is a second-time founder who experienced failure in her first venture and zero if the founder is a new entrant. *Success Before* is a dummy variable for whether the first venture of a second-time entrepreneur went public or was acquired. Results are reported in Panel A for founders with past failure and Panel B for those with past success. In both panel, the sample is split with respect to the past VC financing experience of second-time entrepreneurs. In columns (1) to (3), *Failure Before* and *Success Before* refer to second-timers who did not receive any VC financing in their first venture. Columns (4) to (6) report results from the subsample in which all serial founders have experienced VC financing in their first venture. *VC financing* is a dummy for whether the start-up received a VC financing. The variable *Female* indicates whether the founder is a female. *Time from first job* corresponds to the log of one plus the time since the first experience of the founder. *Elite School* is a dummy variable that is equal to one if the founder attended a top US school. The unit of observation is the company-founder pair. Clustered standard errors at the company level are reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5% and 10% level, respectively.

Panel A: Past Failure

	Successful Exit					
	Past VC Exp			No Past VC Exp		
	(1)	(2)	(3)	(4)	(5)	(6)
Failure Before	-0.013 (0.020)	-0.020 (0.025)	0.017 (0.023)	-0.010 (0.017)	-0.011 (0.023)	0.006 (0.018)
VC Financing	0.217*** (0.005)	0.217*** (0.006)	0.218*** (0.005)	0.217*** (0.005)	0.217*** (0.006)	0.218*** (0.005)
Failure Before × VC Financing			-0.055 (0.038)			-0.044 (0.038)
Female	-0.054*** (0.005)	-0.063*** (0.007)	-0.054*** (0.005)	-0.055*** (0.005)	-0.063*** (0.007)	-0.055*** (0.005)
Time from first job	0.002 (0.002)	-0.001 (0.002)	0.002 (0.002)	0.002 (0.002)	-0.001 (0.002)	0.002 (0.002)
Elite School		0.023*** (0.006)			0.023*** (0.006)	
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Founding Year	Yes	Yes	Yes	Yes	Yes	Yes
State	Yes	Yes	Yes	Yes	Yes	Yes
Highest Degree	No	Yes	No	No	Yes	No
Observations	49,930	29,543	49,930	49,971	29,553	49,971
R ²	0.127	0.136	0.127	0.127	0.135	0.127

Table 11: Performance and Past VC Experience (continued)

Panel A: Past Success

	Successful Exit					
	Past VC Exp			No Past VC Exp		
	(1)	(2)	(3)	(4)	(5)	(6)
Success Before	0.031** (0.013)	0.024 (0.015)	0.018 (0.017)	0.061*** (0.015)	0.085*** (0.018)	0.077*** (0.018)
VC Financing	0.218*** (0.005)	0.218*** (0.006)	0.218*** (0.005)	0.217*** (0.005)	0.217*** (0.006)	0.218*** (0.005)
Success Before \times VC Financing			0.019 (0.024)			-0.034 (0.029)
Female	-0.054*** (0.005)	-0.063*** (0.007)	-0.054*** (0.005)	-0.053*** (0.005)	-0.061*** (0.007)	-0.053*** (0.005)
Time from first job	0.002 (0.002)	-0.001 (0.002)	0.002 (0.002)	0.002 (0.002)	-0.001 (0.002)	0.002 (0.002)
Elite School		0.020*** (0.006)			0.023*** (0.006)	
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Founding Year	Yes	Yes	Yes	Yes	Yes	Yes
State	Yes	Yes	Yes	Yes	Yes	Yes
Highest Degree	No	Yes	No	No	Yes	No
Observations	50,820	30,231	50,820	50,587	29,998	50,587
R ²	0.128	0.136	0.128	0.127	0.136	0.127

Table 12: Differences between previously backed and not backed serial founders

The table reports the results from OLS regressions where the dependent variable is *Past VC Exp*, a dummy variable equal to one if the serial founder experienced VC financing before. Columns (1) to (6) reports results from the main sample of analysis while columns (7) to (12) present results from the sample restricted to focal ventures that are VC-backed. See table 14 for variable descriptions.

	Past VC Exp											
	All						VC-backed					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
PhD	0.030 (0.044)						-0.016 (0.053)					
MBA	0.041 (0.035)						0.050 (0.043)					
Elite School	0.065*** (0.023)						0.019 (0.029)					
STEM	0.045* (0.024)						0.026 (0.029)					
GAI		0.022*** (0.006)						0.007 (0.007)				
Different firms			0.076*** (0.021)						0.024 (0.027)			
Different positions				0.081*** (0.018)						0.040* (0.023)		
Different industries					0.058*** (0.021)						0.006 (0.027)	
First Exp_founder						-0.088*** (0.020)						-0.055** (0.026)
First Exp_Clevel						0.108*** (0.025)						0.104*** (0.030)
First Exp_VP						0.094** (0.038)						0.086* (0.046)
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Founding Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,209	3,300	3,300	3,300	3,300	3,300	1,311	1,796	1,796	1,796	1,796	1,796
R ²	0.066	0.063	0.063	0.065	0.061	0.070	0.071	0.068	0.068	0.069	0.067	0.076

Table 13: Performance of VC-backed Serial Founders and Past VC Experience

The table reports the results from OLS regressions where the dependent variable is: the outcome of the venture in columns (1) and (2), and the average failure tolerance of the venture's first or lead (when defined) VC investors in columns (3) and (4). *Successful Exit* is a dummy variable equal to one if the company successfully exited via an IPO or an M&A. *Failure* is a dummy that takes the value one if the company closed without achieving a successful exit or if it received its last VC financing more than 3 years ago. *VC Failure Tol.* and *VC Failure Tol.2* are average failure tolerance of the venture's first or lead (when defined) VC investors. The failure tolerance measure of a VC corresponds to the average investment duration in past failed projects and the failure tolerance 2 measure represents the average number of rounds of past failed projects to which the VC participated (Tian and Wang, 2014). The variable *Female* indicates whether the founder is a female. The variable *Past VC Exp* indicates whether the founder experienced VC financing before. The unit of observation is the company-founder pair. Clustered standard errors at the company level are reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5% and 10% level, respectively.

	Successful Exit	Failure	VC Failure Tol.	VC Failure Tol.2
	(1)	(2)	(3)	(4)
Female	-0.065 (0.045)	0.036 (0.048)	-0.067 (0.058)	0.005 (0.045)
Any VC Before	0.006 (0.025)	-0.021 (0.025)	0.112*** (0.030)	0.048* (0.025)
Industry	Yes	Yes	Yes	Yes
Founding Year	Yes	Yes	Yes	Yes
State	Yes	Yes	Yes	Yes
Observations	1,796	1,796	1,751	1,751
R ²	0.123	0.053	0.124	0.096

Description of Variables

Table 14: Description of Variables

Variable	Description
Dependent variables	
Founder Again	Dummy variable that is equal to one if the founder started another company (at anytime) after the exit date of the focal firm and zero otherwise.
Next Exp Founder	Dummy variable that is equal to one if the next experience of the founder after the exit date of the focal firm is again a founder experience and zero otherwise.
VC Financing Successful Exit	Dummy variable that is equal to one if the company receives any VC financing and zero otherwise. Dummy variable that is equal to one if the company exited through an IPO or an M&A and zero otherwise.
Failure	Dummy variable that is equal to one if the company closed without achieving a successful exit or if it received its last VC financing more than 3 years ago and zero otherwise.
Key independent variables	
Second-time E	Dummy variable that is equal to one if the company is the founder's second venture.
Failure Before	Dummy variable that is equal to one if the founder experienced failure in the first venture.
Success Before	Dummy variable that is equal to one if the founder experienced a successful exit in the first venture.
Any Failure Before	Dummy variable that is equal to one if the founder experienced failure in any past venture.
Any Success Before	Dummy variable that is equal to one if the founder experienced a successful exit in any past venture.
Female	Dummy variable that is equal to one if the founder is a woman and zero if the founder is a man.
Time from first job	Natural logarithm of one plus the number of years between the first job experience of the founder and the founding of the focal firm.
Elite School	Dummy variable that is equal to one if the founder attended any Elite School (Brown University, Columbia University, Cornell University, Dartmouth College, Duke University, Harvard University, Massachusetts Institute of Technology, Northwestern University, Princeton University, Stanford University, University of California, Berkeley, University of Chicago, University of Pennsylvania and Yale University) and zero otherwise.
MBA	Dummy variable that is equal to one if the founder completed an MBA degree before founding the company.
STEM	Dummy variable that is equal to one if the founder completed any STEM degree before founding the company.
PhD	Dummy variable that is equal to one if the founder completed an PhD degree before founding the company.
Master (non MBA)	Dummy variable that is equal to one if the founder completed a master degree (not including MBA) before founding the company.
Past Founder Experience	Natural logarithm of one plus the number of companies started by the founder before.
Company Exit Age	Age of the company at the exit date in years.
Recession Exit	Dummy variable that is equal to one if the company exited during a recession period (based on NBER Business Cycle Dates)
Non-US Experience	Dummy variable that is equal to one if the founder has any previous work experience outside of the US.
First Exp_founder	Dummy variable that is equal to one if the first job position of the founder is a founder experience.
First Exp_Clevel	Dummy variable that is equal to one if the first job position of the founder is a Clevel position.
First Exp_VP	Dummy variable that is equal to one if the first job position of the founder is a VP position.
First Exp_CEO	Dummy variable that is equal to one if the first job position of the founder is a CEO position.
Different firms	Natural logarithm of one plus the number of companies in which the founder worked before.
Different positions	Natural logarithm of one plus the number of positions under which the founder worked before.
Different industries	Natural logarithm of one plus the number of industries in which the founder worked before.
GAI	General ability index.
GAI 2	General ability index constructed without the variable Founder Before.
VC Failure Tol.	Average failure tolerance of the first VC investors or lead investors (if available) built on the average investment duration in past failed projects to which the VC participated.
VC Failure Tol 2.	Average failure tolerance of the first VC investors or lead investors (if available) built on the average round numbers of past failed projects to which the VC participated.
Main fixed effects	
Industry	Industry of the company: see Appendix 3.7.1 for more details.
Founding Year	Founding year of the focal company.
State	State of the focal company.
Highest Degree	Variable equal to the highest degree completed by the founder before founding the company defined as PhD >Master >Bachelor.

3.7 Appendix

3.7.1 Industry measures

Crunchbase (CB) does not report industry information from major classification systems (SIC or NAICs), it defines industries and industry groups based on its own classification. This latter results in 744 industries corresponding to specific market segments and 47 industry groups that encompass multiple industries. Since CB aims to optimize company's profiles for searches in their platform, industries are constructed in a way that enables CB to attribute multiple industries and industry groups to each company (up to 17 groups). Therefore, I build two industry variables for my analysis. Considering that my study does not require high granularity at industry level, I first use CB industry groups and company descriptions to classify companies into 12 categories close to the 10 sector classification from Refinitiv (VE Primary Industry Minor Group). Based on a keyword approach, I reclassify industries to allocate one main industry per company based on the company's description. Then, I use a machine learning approach to replicate Refinitiv classification. As results from the two approaches are quite similar, I use the first one in the main regressions and I replicate the analysis with the second industry variable. More details for each classification are exposed below. For the classifications, I use the initial sample of the data and not the main analysis sample that is more restricted (with 119 082 company-level observations).

Industry classification: keyword approach

From the industry groups provided by Crunchbase and companies' descriptions, I classify startups into the following 11 categories: Biotechnology, Medical/Health, Computer Hardware, Computer Software, Internet Specific/IT, Communications and Media, Industrial/Energy, Financial Services, Consumer Related, Semiconductors/Electronics and Others. I first start by gathering some CB industry groups and ignoring redundant ones. I then use companies' descriptions to categorize them in each of the groups using text-based analysis. Table A1 reports the keywords defined for 8 categories. The keywords are carefully selected to avoid misclassifications and lead to a very conservative classification. When a company is not assigned to an industry after the searches but has a unique CB industry group corresponding to one of the eleven industries, then it is assumed to belong to this industry. In a sense, I revisit the CB industry classification to aggregate industry groups as accurately as possible. Once an industry is identified for a company, the classification

process stops but follows a specific rule with respect to internet specific and software categories²³. These are dominant industries, i.e., if their keywords are identified in a description, although another industry was allocated before, it will be replaced. This enables me to allocate an industry to half of the companies. For the remaining firms, if CB associates a unique industry group, I keep this group (the CB groups being previously reclassified to avoid redundancy and to be in line with the new classification). This leaves me with 30% missing industries. For the remaining 30%, I use the following ordering rule: Internet services > Software > Biotech > Medical/Health > Hardware > Financial Services Real Estate > Energy Manufacturing | Real estate and (E|M) > Sales and Marketing > Media and Entertainment > Consumer Related > IT.

Industry classification: Machine learning approach

To complement the previous classification, I proceed to multiple other classifications with machine learning. I use a Refinitiv dataset including company business descriptions and the 10-sector classification of interest to train the models under supervised learning. Finally, I select the classification obtained with the linear support vector machine algorithm (with one vs rest classification) which performed better than a naïve bayes classifier.

²³With Internet services > Software > Other Industries

3.7.2 Additional tables

Table A1: Industry Classification Keywords

Industry	Unique keywords
Biotech	biopharm, bioscience, biotech, biotherap
Medical/Health	disease, healthcare, medical, medicine, patient, pharma
Hardware	data storage, embedded systems, flash storage, hardware, integrated circuits
Software	app, appli, apps, software
Internet Specific	browser, cloud, e-commerce, e-learning, internet, online, search, social media, social network, web
Information Technology	communication technology, information service, information technology, it company, it infrastructure, it services, it solutions, it support, technology solution
Industrial/Energy	energy, manufactur
Financial Services	bank, financial, financial service, lending, real estate, insurance, investment, payments

Figure A1: Industry Classification Distribution: The figure reports the share of each industry in the two classifications (based on an unrestricted sample of US companies containing 119 082 companies). ML Classif, in blue, refers to classification obtained with the machine learning approach. Classif1, in orange, refers to the keyword-based textual analysis approach.

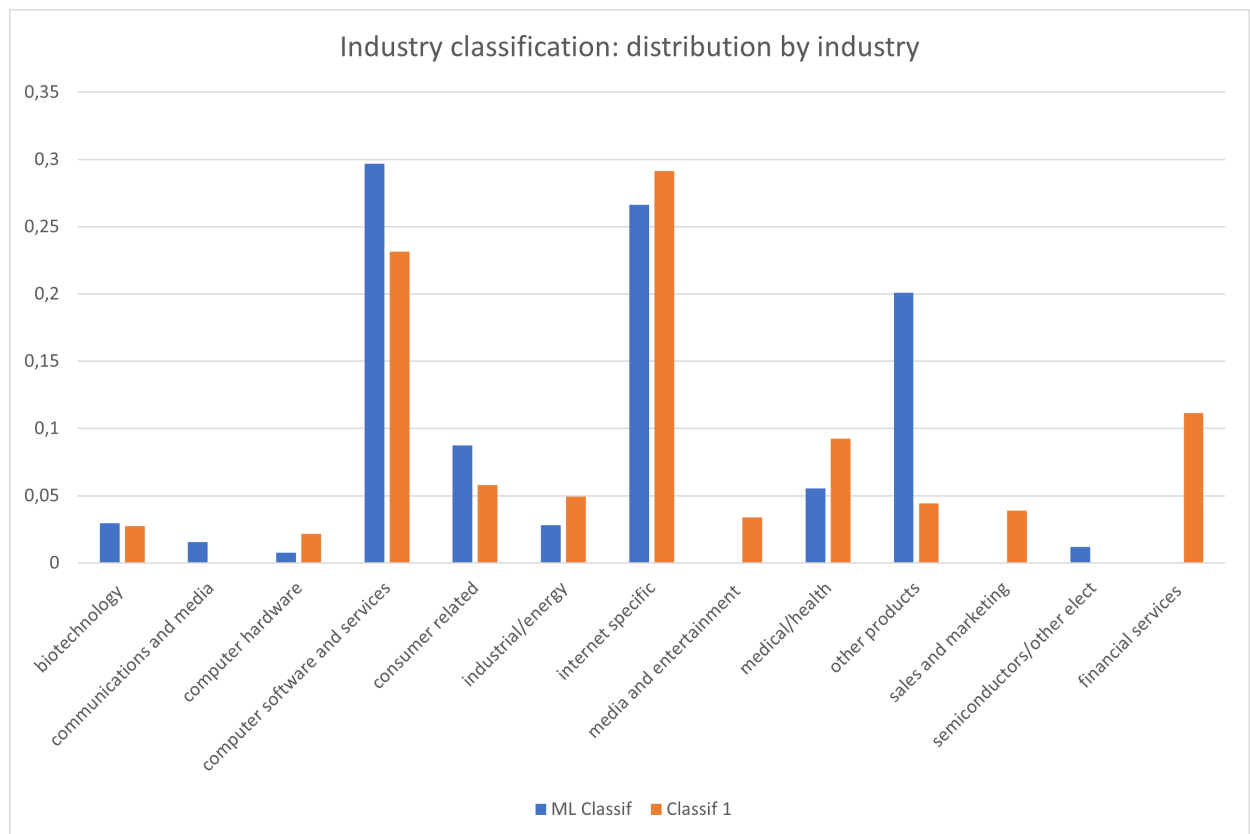


Table A2: VC Financing and Past Experience - all serial founders

The table reports the results of a linear probability model where the dependent variable is a dummy variable equal to one if the company receives VC financing. *Founder Before* is a dummy variable indicating whether the founder is a serial entrepreneur. *Any Failure Before* is a dummy variable that takes the value of one if the founder experienced a failure in a past venture. *Any Success Before* is a dummy variable for whether the founder experienced a successful exit (through IPO or M&A) in a past venture. The variable *Female* indicates whether the founder is a female. *Time from first job* corresponds to the log of one plus the time since the first experience of the founder. *GAI 2* refers to the general ability index of the founder. *Elite School* is a dummy for whether the founder attended a top US school. To keep first-time entrepreneurs as the reference group, past successful founders are excluded from the sample in columns (3) and (4), and founders with a failure experience are excluded from the sample in columns (5) and (6). The unit of observation is the company-founder pair. Clustered standard errors at the company level are reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5% and 10% level, respectively.

	VC Financing					
	(1)	(2)	(3)	(4)	(5)	(6)
Founder Before	0.058*** (0.008)	0.059*** (0.010)				
Any Failure Before			-0.014 (0.013)	-0.015 (0.016)		
Any Success Before					0.086*** (0.009)	0.084*** (0.011)
Female	-0.017** (0.007)	-0.001 (0.008)	-0.018*** (0.007)	-0.002 (0.009)	-0.017** (0.007)	-0.002 (0.008)
Time from first job	0.020*** (0.003)	0.019*** (0.004)	0.023*** (0.003)	0.021*** (0.004)	0.018*** (0.003)	0.017*** (0.004)
GAI 2	0.007*** (0.002)	0.001 (0.002)	0.006*** (0.002)	0.0001 (0.002)	0.009*** (0.002)	0.002 (0.002)
Elite School		0.092*** (0.006)		0.095*** (0.007)		0.089*** (0.006)
MBA		0.030** (0.012)		0.033** (0.013)		0.027** (0.013)
STEM		0.052*** (0.007)		0.053*** (0.008)		0.052*** (0.007)
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Founding Year	Yes	Yes	Yes	Yes	Yes	Yes
State	Yes	Yes	Yes	Yes	Yes	Yes
Highest Degree	No	Yes	No	Yes	No	Yes
Observations	55,273	33,396	51,247	30,458	53,759	32,402
R ²	0.078	0.093	0.070	0.086	0.080	0.095

Table A3: VC Financing and Past VC Experience - all serial founders

The table reports the results of a linear probability model where the dependent variable is a dummy variable equal to one if the company receives VC financing. *Founder Before* is a dummy variable indicating whether the founder is a serial entrepreneur (with past venture outcomes realized by the time of the founding of the focal firm-the sample excludes portfolio entrepreneurs). The sample is split with respect to the past VC financing experience of serial founders. In columns (1) and (2), the variable *Founder Before* refers to serial entrepreneurs who did not receive any VC financing in their past ventures. Columns (3) and (4) report results from the subsample in which all serial founders have experienced VC financing before. The variable *Female* indicates whether the founder is a female. *Time from first job* corresponds to the log of one plus the time since the first experience of the founder. *GAI 2* refers to the general ability index of the founder. *Elite School* is a dummy variable that is equal to one if the founder attended a top US school. Columns (2) and (4) additionally contain controls for *Elite School*, *MBA* and *STEM* degrees. The unit of observation is the company-founder pair. Clustered standard errors at the company level are reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5% and 10% level, respectively.

	VC Financing			
	No Past VC Exp.		Any Past VC Exp.	
	(1)	(2)	(3)	(4)
Founder Before	-0.022** (0.011)	-0.008 (0.013)	0.119*** (0.010)	0.106*** (0.012)
Female	-0.018*** (0.007)	-0.002 (0.009)	-0.018*** (0.007)	-0.002 (0.008)
Time from first job	0.019*** (0.003)	0.018*** (0.004)	0.023*** (0.003)	0.021*** (0.004)
GAI 2	0.009*** (0.002)	0.002 (0.002)	0.005*** (0.002)	0.0003 (0.002)
Industry	Yes	Yes	Yes	Yes
Founding Year	Yes	Yes	Yes	Yes
State	Yes	Yes	Yes	Yes
Highest Degree	No	Yes	No	Yes
Observations	52,031	30,987	52,744	31,688
R ²	0.070	0.086	0.081	0.095

Table A4: VC Financing, Past VC Experience and Past Outcome - all serial founders

The table reports the results of a linear probability model where the dependent variable is a dummy variable equal to one if the company receives VC financing. The sample is split with respect to the past VC financing experience of serial entrepreneurs. *Any Failure Before* is a dummy variable that takes the value of one if a serial founder experienced a failure before. *Any Success Before* is a dummy variable for whether any past venture of a serial entrepreneur went public or was acquired. In columns (1) and (2), these variables refer to past outcomes of serial entrepreneurs who did not receive any VC financing in the past. Columns (3) and (4) report results from the subsample in which all serial founders have experienced VC financing in any previous venture. The reference group is first-time entrepreneurs in all the regressions as serial founders without any failure before are excluded from the sample in columns (1) and (2), and those without any success before are excluded from the sample in columns (3) and (4). Thus, *Failure Before* and *Success Before* are equal to zero when the founder is a new entrant. The variable *Female* indicates whether the founder is a female. *Time from first job* corresponds to the log of one plus the time since the first experience of the founder. *GAI 2* refers to the general ability index of the founder. The unit of observation is the company-founder pair. Clustered standard errors at the company level are reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5% and 10% level, respectively.

	VC Financing			
	No Past VC Exp.		Past VC Exp.	
	(1)	(2)	(3)	(4)
Any Failure Before	-0.081*** (0.018)		0.041** (0.018)	
Any Success Before		0.004 (0.013)		0.143*** (0.011)
Female	-0.018*** (0.007)	-0.019*** (0.007)	-0.019*** (0.007)	-0.017** (0.007)
Time from first job	0.020*** (0.004)	0.018*** (0.003)	0.023*** (0.004)	0.022*** (0.003)
GMA 2	0.009*** (0.002)	0.010*** (0.002)	0.006*** (0.002)	0.006*** (0.002)
Industry	Yes	Yes	Yes	Yes
Founding Year	Yes	Yes	Yes	Yes
State	Yes	Yes	Yes	Yes
Observations	50,306	51,260	50,443	52,001
R ²	0.070	0.071	0.071	0.082

Table A5: VC Financing, Past Experience and Alternative Financing Sources

The table reports the results of a linear probability model where the dependent variable is a dummy variable equal to one if the company receives VC financing. *Second-time E* is a dummy variable indicating whether the founder is a second-time entrepreneur. *Failure Before* is a dummy variable that takes the value of one if a second-time founder experienced a failure in her first venture. *Success Before* is a dummy for whether the first venture of a second-time entrepreneur went public or was acquired. The variable *Female* indicates whether the founder is a female. *Time from first job* corresponds to the log of one plus the time since the first job of the founder. *GAI 2* refers to the general ability index of the founder. *Elite School* is a dummy variable that is equal to one if the founder attended a top US school. *Angel Financing*, *Debt Financing* and *Crowdfunding* are dummies for whether the company use these alternative financing sources. To keep first-timers as the reference group, past successful founders are excluded from the sample in columns (3) and (4), and founders with a failure experience are excluded from the sample in columns (5) and (6). The unit of observation is the company-founder pair. Clustered standard errors at the company level are reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5% and 10% level, respectively.

	VC Financing			
	(1)	(2)	(3)	(4)
Second-time E	-0.005 (0.012)	-0.0001 (0.015)		
Failure Before			-0.050** (0.021)	
Success Before				0.014 (0.014)
Female	-0.011* (0.006)	-0.001 (0.008)	-0.011* (0.006)	-0.011* (0.006)
Time from first job	0.013*** (0.003)	0.014*** (0.004)	0.015*** (0.003)	0.013*** (0.003)
GAI 2	0.007*** (0.002)	0.002 (0.002)	0.006*** (0.002)	0.007*** (0.002)
Angel Financing	0.457*** (0.006)	0.442*** (0.007)	0.456*** (0.006)	0.456*** (0.006)
Debt Financing	0.229*** (0.011)	0.226*** (0.012)	0.228*** (0.011)	0.230*** (0.011)
Crowdfunding	-0.062*** (0.022)	-0.061** (0.029)	-0.062*** (0.022)	-0.065*** (0.022)
Industry	Yes	Yes	Yes	Yes
Founding Year	Yes	Yes	Yes	Yes
State	Yes	Yes	Yes	Yes
Highest Degree	No	Yes	No	No
Observations	51,056	30,272	49,971	50,587
R ²	0.246	0.256	0.245	0.246

Table A6: Performance and Past Failure Experience - restricted failure measure

The table reports the results of a linear probability model where the dependent variable is the outcome of the company. *Successful Exit* is a dummy variable equal to one if the company successfully exited via an IPO or an M&A. *Failure* is a dummy that takes the value one if the company closed without achieving a successful exit (IPO or M&A). *Failure Before* is a dummy variable that takes the value of one if the founder is a second-time founder who experienced failure in her first venture and zero if the founder is a new entrant. *VC financing* is a dummy for whether the start-up received a VC financing. The variable *Female* indicates whether the founder is a female. *Time from first job* corresponds to the log of one plus the time since the first experience of the founder. *Elite School* is a dummy variable that is equal to one if the founder attended a top US school. The unit of observation is the company-founder pair. Clustered standard errors at the company level are reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5% and 10% level, respectively.

	Successful Exit			Failure		
	(1)	(2)	(3)	(4)	(5)	(6)
Failure Before	0.006 (0.016)	0.0002 (0.021)	0.017 (0.018)	0.023 (0.020)	0.029 (0.026)	0.074*** (0.028)
VC Financing	0.217*** (0.005)	0.217*** (0.006)	0.218*** (0.005)	0.149*** (0.006)	0.121*** (0.007)	0.150*** (0.006)
Failure Before × VC Financing			-0.025 (0.034)			-0.104*** (0.040)
Female	-0.055*** (0.005)	-0.064*** (0.007)	-0.055*** (0.005)	0.013* (0.007)	0.039*** (0.009)	0.013* (0.007)
Time from first job	0.002 (0.002)	-0.001 (0.002)	0.002 (0.002)	-0.023*** (0.002)	-0.022*** (0.003)	-0.023*** (0.002)
Elite School		0.023*** (0.006)			-0.009 (0.007)	
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Founding Year	Yes	Yes	Yes	Yes	Yes	Yes
State	Yes	Yes	Yes	Yes	Yes	Yes
Highest Degree	No	Yes	No	No	Yes	No
Observations	50,119	29,657	50,119	46,172	27,337	46,172
R ²	0.127	0.135	0.127	0.056	0.050	0.056

Table A7: Differences Among Second-timers based on Past VC experience

The table presents characteristics differences between second-time entrepreneurs with respect to their past VC financing experience. Panel A compares founders' educational background, panel B focuses on their career, panel C describe past venture characteristics and panel D provides the focal venture's characteristics. The mean and number of observations are reported for each of group as well as differences in means and their t-stat.

	All		No Past VC Exp		Past VC Exp		difference	t-stat
	N	Mean	N	Mean	N	Mean		
Panel A. Founder characteristics								
Female	3,300	0.057	1,554	0.057	1,746	0.056	0.00114	(0.14)
PhD	2,209	0.063	993	0.050	1,216	0.073	-0.0228*	(-2.20)
MBA	2,209	0.110	993	0.094	1,216	0.124	-0.0305*	(-2.28)
Master (non MBA)	2,209	0.134	993	0.123	1,216	0.142	-0.0194	(-1.33)
Bachelor	2,209	0.545	993	0.534	1,216	0.554	-0.0205	(-0.96)
STEM	2,209	0.330	993	0.298	1,216	0.356	-0.0580**	(-2.89)
Elite School	2,209	0.388	993	0.337	1,216	0.428	-0.0911***	(-4.39)
Panel B. Founder Career								
First Experience								
First experience_founder	3,300	0.738	1,554	0.777	1,746	0.704	0.0728***	(4.76)
First experience_VP	3,300	0.058	1,554	0.047	1,746	0.068	-0.0212**	(-2.60)
First experience_C level	3,300	0.140	1,554	0.113	1,746	0.164	-0.0511***	(-4.23)
First experience_CEO	3,300	0.268	1,554	0.279	1,746	0.258	0.0203	(1.32)
Time from first experience (years)	3,300	10.456	1,554	10.323	1,746	10.573	-0.250	(-1.01)
Overall experience before the focal firm								
Different firms	3,300	2.114	1,554	1.986	1,746	2.229	-0.243***	(-4.01)
Different positions	3,300	2.066	1,554	1.903	1,746	2.212	-0.309***	(-5.01)
Different industry	3,300	1.179	1,554	1.125	1,746	1.226	-0.101**	(-2.98)
Different industry (founded)	3,300	0.668	1,554	0.677	1,746	0.661	0.0160	(0.95)
GAI (General Ability Index)	3,300	1.327	1,554	1.206	1,746	1.435	-0.228***	(-4.39)
Overall experience before the first venture								
Different firms	3,300	0.492	1,554	0.406	1,746	0.568	-0.162***	(-4.31)
Different positions	3,300	0.558	1,554	0.457	1,746	0.648	-0.191***	(-4.73)
Different industry	3,300	0.310	1,554	0.257	1,746	0.357	-0.0994***	(-4.18)
GAI (General Ability Index)	3,300	0.437	1,554	0.261	1,746	0.593	-0.332***	(-4.63)
Panel C. Past venture characteristics								
Financing								
Any Angel Financing Before	3,300	0.240	1,554	0.125	1,746	0.343	-0.218***	(-15.14)
Any Debt Financing Before	3,300	0.052	1,554	0.030	1,746	0.071	-0.0408***	(-5.30)
Any Crowdfunding Before	3,300	0.002	1,554	0.001	1,746	0.003	-0.00222	(-1.49)
Any Financing Before	3,300	0.601	1,554	0.152	1,746	1.000	-0.848***	(-98.72)
Outcome (realized before focal firm)								
Any Success Before	3,300	0.728	1,554	0.698	1,746	0.755	-0.0567***	(-3.66)
Any Exit IPO Before	3,300	0.116	1,554	0.122	1,746	0.112	0.00994	(0.89)
Any Exit Acq Before	3,300	0.612	1,554	0.577	1,746	0.643	-0.0666***	(-3.93)
Any Failure Before	3,300	0.187	1,554	0.268	1,746	0.115	0.154***	(11.53)
Any Failure (operating) Before	3,300	0.272	1,554	0.302	1,746	0.245	0.0567***	(3.66)

**Table A7: Differences Among Second-timers based on Past VC experience
(continued)**

	All		No Past VC Exp		Past VC Exp		difference	t-stat
	N	Mean	N	Mean	N	Mean		
Panel D. Startup characteristics								
Geography								
Company located in CA	3,300	0.487	1,554	0.427	1,746	0.540	-0.112***	(-6.48)
Company located in NY	3,300	0.140	1,554	0.144	1,746	0.136	0.00841	(0.70)
Company located in MA	3,300	0.067	1,554	0.052	1,746	0.081	-0.0286**	(-3.28)
Industry								
Internet/Computer	3,300	0.657	1,554	0.651	1,746	0.663	-0.0127	(-0.76)
Biotechnology	3,300	0.027	1,554	0.015	1,746	0.037	-0.0218***	(-3.86)
Medical/Health	3,300	0.080	1,554	0.073	1,746	0.085	-0.0120	(-1.27)
Financial Services	3,300	0.067	1,554	0.079	1,746	0.056	0.0236**	(2.71)
Financing								
VC financing	3,300	0.544	1,554	0.44	1,746	0.638	-0.197***	(-11.62)
Angel Financing	3,300	0.302	1,554	0.274	1,746	0.326	-0.0523**	(-3.27)
Crowdfunding	3,300	0.062	1,554	0.066	1,746	0.058	0.00843	(1.00)
Debt Financing	3,300	0.010	1,554	0.010	1,746	0.011	-0.00123	(-0.35)
First financing amount	1,495	6.692	630	4.393	865	8.366	-3.972***	(-3.69)
First vc financing amount	1,421	7.168	579	4.894	842	8.731	-3.838***	(-3.41)
Total funding	2,087	67.750	893	51.871	1,194	79.627	-27.76**	(-3.05)
Nb of rounds	2,373	3.354	1,022	3.216	1,351	3.458	-0.242*	(-2.19)
VC Failure tolerance	1,751	0.690	658	0.632	1,093	0.725	-0.0936**	(-3.03)
VC Failure tolerance 2	1,751	1.330	658	1.306	1,093	1.345	-0.0392	(-1.57)
Time between first to second round	1,665	1.285	674	1.329	991	1.255	0.0743	(1.35)
Same investor	3,300	0.082	1,554	0.000	1,746	0.154	-	-
Same investor was lead	3,300	0.032	1,554	0.000	1,746	0.060	-	-
Same investor is lead	3,300	0.039	1,554	0.000	1,746	0.073	-	-
Same investor as first	3,300	0.082	1,554	0.000	1,746	0.154	-	-
Same investor as first (lead)	3,300	0.032	1,554	0.000	1,746	0.060	-	-
Outcome								
Successful Exit	3,300	0.260	1,554	0.248	1,746	0.271	-0.0232	(-1.51)
Exit_IPO	3,300	0.031	1,554	0.023	1,746	0.038	-0.0153*	(-2.55)
Exit_Acq	3,300	0.229	1,554	0.225	1,746	0.233	-0.00788	(-0.54)
Failure	3,300	0.131	1,554	0.140	1,746	0.124	0.0159	(1.35)
Failure_Operating	3,141	0.289	1,455	0.295	1,686	0.284	0.0107	(0.66)

Table A8: Performance and Founder Characteristics

The table reports the results of a linear probability model where the dependent variable is the outcome of the company. *Successful Exit* is a dummy variable equal to one if the company exits via an IPO or an M&A. *Failure* is a dummy that takes the value one if the company closes without achieving a successful exit or if it received its last VC financing more than 3 years ago. See table 14 for variable descriptions. The unit of observation is the company-founder pair. Clustered standard errors at the company level are reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5% and 10% level, respectively.

	Successful Exit					Failure				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Female	-0.064*** (0.007)	-0.059*** (0.005)	-0.060*** (0.005)	-0.060*** (0.005)	-0.058*** (0.005)	0.040*** (0.009)	0.011 (0.007)	0.011 (0.007)	0.012* (0.007)	0.013* (0.007)
PhD	0.027** (0.013)					-0.039*** (0.013)				
MBA	0.022*** (0.008)					-0.026*** (0.009)				
Elite School	0.040*** (0.006)					0.003 (0.007)				
STEM	0.027*** (0.006)					-0.021*** (0.007)				
Different firms		0.025*** (0.004)								
Different positions			0.023*** (0.004)							
Different industries				0.012*** (0.005)						
First Exp_founder					-0.016*** (0.004)					0.031*** (0.005)
First Exp_Clevel					0.072*** (0.005)					0.023*** (0.006)
First Exp_VP					0.061*** (0.009)					0.001 (0.009)
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Founding Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	31,488	52,802	52,802	52,802	52,802	29,095	48,729	48,729	48,729	48,729
R ²	0.077	0.066	0.066	0.065	0.070	0.032	0.032	0.032	0.031	0.032

Table A9: Performance of non-VC-backed Serial Founders and Past VC Experience

The table reports the results of a linear probability model where the dependent variable is the outcome of the company. *Successful Exit* is a dummy variable equal to one if the company exits via an IPO or an M&A. *Failure* is a dummy that takes the value one if the company closes without achieving a successful exit or if it received its last VC financing more than 3 years ago. The variable *Past VC Exp* indicates whether the founder experienced VC financing before. The variable *Female* indicates whether the founder is a female. *Time from first job* corresponds to the log of one plus the time since the first experience of the founder. *Elite School* is a dummy variable that is equal to one if the founder attended a top US school. The unit of observation is the company-founder pair. Clustered standard errors at the company level are reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5% and 10% level, respectively.

	Successful Exit		Failure	
	(1)	(2)	(3)	(4)
Past VC Exp	-0.037* (0.019)	-0.055** (0.026)	0.006 (0.026)	0.002 (0.035)
Female	-0.018 (0.036)	-0.027 (0.049)	0.010 (0.053)	0.007 (0.069)
Time from first job	-0.012 (0.015)	-0.032 (0.021)	-0.010 (0.020)	-0.028 (0.028)
Elite School		0.032 (0.030)		-0.017 (0.039)
Industry	Yes	Yes	Yes	Yes
Founding Year	Yes	Yes	Yes	Yes
State	Yes	Yes	Yes	Yes
Highest Degree	No	Yes	No	Yes
Observations	1,504	898	1,345	806
R ²	0.084	0.115	0.088	0.118

Bibliography

- Agarwal, S. and Hauswald, R. (2010). Distance and private information in lending. *The Review of Financial Studies*, 23(7):2757–2788.
- Aghion, P. and Howitt, P. (1992). A model of growth through creative destruction. *Econometrica*, 60(2):323–351.
- Agrawal, A. and Goldfarb, A. (2008). Restructuring research: Communication costs and the democratization of university innovation. *American Economic Review*, 98(4):1578–90.
- Amornsiripanitch, N., Gompers, P., Hu, G., Levinson, W., and Mukharlyamov, V. (2022). Failing just fine: Assessing careers of venture capital-backed entrepreneurs via a non-wage measure. *Working Paper*.
- Amornsiripanitch, N., Gompers, P. A., and Xuan, Y. (2019). More than money: Venture capitalists on boards. *The Journal of Law, Economics, and Organization*, 35(3):513–543.
- Antweiler, W., Brander, J., and Amit, R. (2002). Venture-Capital Syndication: Improved Venture Selection vs. The Value-Added Hypothesis. *Journal of Economics Management Strategy*, 11:423–452.
- Astebro, T., Herz, H., Nanda, R., and Weber, R. A. (2014). Seeking the roots of entrepreneurship: Insights from behavioral economics. *Journal of Economic Perspectives*, 28(3):49–70.
- Barber, B. M. and Yasuda, A. (2017). Interim fund performance and fundraising in private equity. *Journal of Financial Economics*, 124(1):172–194.
- Bellucci, A., Borisov, A., Gucciardi, G., and Zazzaro, A. (2022). The reallocation effects of COVID-19: Evidence from venture capital investments around the world. *Journal of Banking Finance*, page 106443.
- Bénabou, R. and Tirole, J. (2002). Self-confidence and personal motivation. *The quarterly journal of economics*, 117(3):871–915.
- Bengtsson, O. (2013). Relational venture capital financing of serial founders. *Journal of Financial Intermediation*, 22(3):308–334.
- Bengtsson, O. and Ravid, S. A. (2009). The Geography of Venture Capital Contracts.

- Berger, A. N., Miller, N. H., Petersen, M. A., Rajan, R. G., and Stein, J. C. (2005). Does function follow organizational form? evidence from the lending practices of large and small banks. *Journal of Financial Economics*, 76(2):237–269.
- Bernstein, S., Giroud, X., and Townsend, R. R. (2016). The impact of venture capital monitoring. *The Journal of Finance*, 71(4):1591–1622.
- Bernstein, S., Korteweg, A., and Laws, K. (2017). Attracting early-stage investors: Evidence from a randomized field experiment. *The Journal of Finance*, 72(2):509–538.
- Bottazzi, L., Da Rin, M., and Hellmann, T. (2008). Who are the active investors?: Evidence from venture capital. *Journal of Financial Economics*, 89(3):488–512.
- Buffington, C., Dennis, C., Dinlersoz, E., Foster, L., Klimek, S., et al. (2020). Measuring the effect of COVID-19 on U.S. small businesses: The small business pulse survey.
- Burchell, B., Hughes, A., et al. (2006). *The stigma of failure: An international comparison of failure tolerance and second chancing*, volume 334. Centre for Business Research, University of Cambridge.
- Busenitz, L. W. and Barney, J. B. (1997). Differences between entrepreneurs and managers in large organizations: Biases and heuristics in strategic decision-making. *Journal of business venturing*, 12(1):9–30.
- Bygrave, W. D. (1987). Syndicated investments by venture capital firms: A networking perspective. *Journal of Business Venturing*, 2(2):139–154.
- Cahn, C., Girotti, M., and Landier, A. (2021). Entrepreneurship and information on past failures: A natural experiment. *Journal of Financial Economics*, 141(1):102–121.
- Camerer, C. and Lovallo, D. (1999). Overconfidence and excess entry: An experimental approach. *The American Economic Review*, 89(1):306–318.
- Casamatta, C. and Haritchabalet, C. (2007). Experience, Screening and Syndication in Venture Capital Investments. (443).
- Cassar, G. (2010). Are individuals entering self-employment overly optimistic? an empirical test of plans and projections on nascent entrepreneur expectations. *Strategic Management Journal*, 31(8):822–840.
- Catherine, S. (2022). Keeping options open: What motivates entrepreneurs? *Journal of Financial Economics*, 144(1):1–21.
- Chakraborty, I. and Ewens, M. (2018). Managing performance signals through delay: Evidence from venture capital. *Management Science*, 64(6):2875–2900.
- Chemla, G. and Tinn, K. (2020). Learning through crowdfunding. *Management Science*, 66(5):1783–1801.

- Chemmanur, T. J., Krishnan, K., and Nandy, D. K. (2011). How does venture capital financing improve efficiency in private firms? a look beneath the surface. *The Review of Financial Studies*, 24(12):4037–4090.
- Chen, H., Gompers, P., Kovner, A., and Lerner, J. (2010). Buy local? The geography of Venture Capital. *Journal of Urban Economics*, 67(1):90–102.
- Cooper, A. C., Woo, C. Y., and Dunkelberg, W. C. (1988). Entrepreneurs’ perceived chances for success. *Journal of business venturing*, 3(2):97–108.
- Cumming, D. and Dai, N. (2010). Local bias in venture capital investments. *Journal of Empirical Finance*, 17(3):362–380.
- Custódio, C., Ferreira, M. A., and Matos, P. (2013). Generalists versus specialists: Lifetime work experience and chief executive officer pay. *Journal of Financial Economics*, 108(2):471–492.
- Custódio, C., Ferreira, M. A., and Matos, P. (2017). Do general managerial skills spur innovation? *Management Science*, 65(2):459–476.
- Dalle, J.-M., den Besten, M., and Menon, C. (2017). Using crunchbase for economic and managerial research. *Working Paper*.
- De Meza, D. and Southey, C. (1996). The borrower’s curse: Optimism, finance and entrepreneurship. *The Economic Journal*, 106(435):375–386.
- Ding, W. W., Levin, S. G., Stephan, P. E., and Winkler, A. E. (2010). The impact of information technology on academic scientists’ productivity and collaboration patterns. *Management Science*, 56(9):1439–1461.
- Dutton, K. A. and Brown, J. D. (1997). Global self-esteem and specific self-views as determinants of people’s reactions to success and failure. *Journal of personality and social psychology*, 73(1):139.
- Ederer, F. and Manso, G. (2013). Is pay for performance detrimental to innovation? *Management Science*, 59(7):1496–1513.
- Efrat, R. (2006). The evolution of bankruptcy stigma. *Theoretical inquiries in Law*, 7(2):365–393.
- Elul, R. and Gottardi, P. (2015). Bankruptcy: Is it enough to forgive or must we also forget? *American Economic Journal: Microeconomics*, 7(4):294–338.
- Ewens, M. and Marx, M. (2018). Founder replacement and startup performance. *The Review of Financial Studies*, 31(4):1532–1565.
- Ferrati, F. and Muffatto, M. (2020). Using crunchbase for research in entrepreneurship: data content and structure. *Working Paper*.
- Forman, C., Goldfarb, A., and Greenstein, S. (2005). How did location affect adoption of the commercial internet? global village vs. urban leadership. *Journal of urban Economics*, 58(3):389–420.

- Forman, C. and Zeebroeck, N. v. (2012). From wires to partners: How the Internet has fostered R&D collaborations within firms. *Management science*, 58(8):1549–1568.
- Gompers, P., Gornall, W., Kaplan, S. N., and Strebulaev, I. A. (2021). Venture Capitalists and COVID-19. *Journal of Financial and Quantitative Analysis*, 56(7):2474–2499.
- Gompers, P., Kovner, A., Lerner, J., and Scharfstein, D. (2008). Venture capital investment cycles: The impact of public markets. *Journal of Financial Economics*, 87(1):1–23.
- Gompers, P., Kovner, A., Lerner, J., and Scharfstein, D. (2010). Performance persistence in entrepreneurship. *Journal of Financial Economics*, 96(1):18–32.
- Gompers, P. and Lerner, J. (2000). Money chasing deals? The impact of fund inflows on private equity valuation. *Journal of Financial Economics*, 55(2):281–325.
- Gompers, P. A., Gornall, W., Kaplan, S., and Strebulaev, I. A. (2020). How do venture capitalists make decisions? *Journal of Financial Economics*, 135(1):169–190.
- Gompers, Paul A. and Mukharlyamov, V. and Xuan, Y. (2016). The cost of friendship. *Journal of Financial Economics*, 119(3):626–644.
- Gorman, M. and Sahlman, W. A. (1989). What do venture capitalists do? *Journal of Business Venturing*, 4(4):231–248.
- Gromb, D. and Scharfstein, D. (2002). Entrepreneurship in equilibrium. Working Paper 9001, National Bureau of Economic Research.
- Hall, R. E. and Woodward, S. E. (2010). The burden of the nondiversifiable risk of entrepreneurship. *American Economic Review*, 100(3):1163–94.
- Hamilton, B. H. (2000). Does entrepreneurship pay? an empirical analysis of the returns to self-employment. *Journal of Political Economy*, 108(3):604–631.
- Han, P., Liu, C., and Tian, X. (2022). The Death of Distance? COVID-19 Lockdown and Venture Capital Investment.
- Hellmann, T. and Puri, M. (2002). Venture capital and the professionalization of start-up firms: Empirical evidence. *The Journal of Finance*, 57(1):169–197.
- Hochberg, Y. V., Ljungqvist, A., and Lu, Y. (2007). Whom You Know Matters: Venture Capital Networks and Investment Performance. *The Journal of Finance*, 62(1):251–301.
- Hochberg, Y. V., Ljungqvist, A., and Lu, Y. (2010). Networking as a Barrier to Entry and the Competitive Supply of Venture Capital. *The Journal of Finance*, 65(3):829–859.
- Howell, S., Lerner, J., Nanda, R., and Townsend, R. (2020). How Resilient is Venture-Backed Innovation? Evidence from Four Decades of U.S. Patenting. *NBER Working Paper*.

- Hsu, D. H. (2006). Venture capitalists and cooperative start-up commercialization strategy. *Management Science*, 52(2):204–219.
- Hsu, D. H. (2007). Experienced entrepreneurial founders, organizational capital, and venture capital funding. *Research Policy*, 36:722–741.
- Hu, A. and Ma, S. (2021). Persuading investors: A video-based study.
- Hurst, E. and Lusardi, A. (2004). Liquidity constraints, household wealth, and entrepreneurship. *Journal of Political Economy*, 112(2):319–347.
- Hvide, H. K. and Panos, G. A. (2014). Risk tolerance and entrepreneurship. *Journal of Financial Economics*, 111(1):200–223.
- Kaplan, S. N., Sensoy, B. A., and Stromberg, P. (2009). Should investors bet on the jockey or the horse? evidence from the evolution of firms from early business plans to public companies. *The Journal of Finance*, 64(1):75–115.
- Kaplan, S. N. and Stromberg, P. (2001). Venture capitals as principals: Contracting, screening, and monitoring. *American Economic Review*, 91(2):426–430.
- Kaplan, S. N. and Stromberg, P. (2004). Characteristics, contracts, and actions: Evidence from venture capitalist analyses. *The Journal of Finance*, 59(5):2177–2210.
- Kerr, W. R. and Nanda, R. (2010). Banking deregulations, financing constraints and firm entry size. *Journal of the European Economic Association*, 8(2/3):582–593.
- Kerr, W. R., Nanda, R., and Rhodes-Kropf, M. (2014). Entrepreneurship as experimentation. *Journal of Economic Perspectives*, 28(3):25–48.
- Kihlstrom, R. E. and Laffont, J.-J. (1979). A general equilibrium entrepreneurial theory of firm formation based on risk aversion. *Journal of Political Economy*, 87(4):719–748.
- Kortum, S. and Lerner, J. (2000). Assessing the contribution of venture capital to innovation. *The RAND Journal of Economics*, 31(4):674–692.
- Kovbasyuk, S. and Spagnolo, G. (2018). Memory and markets. *Available at SSRN 2756540*.
- Lafontaine, F. and Shaw, K. (2016). Serial entrepreneurship: Learning by doing? *Journal of Labor Economics*, 34(S2):S217–S254.
- Landier, A. (2005). Entrepreneurship and the stigma of failure. *Working Paper*.
- Landier, A. and Thesmar, D. (2009). Financial contracting with optimistic entrepreneurs. *The Review of Financial Studies*, 22(1):117–150.
- Lazear, E. (2005). Entrepreneurship. *Journal of Labor Economics*, 23(4):649–680.

- Lerner, J. (1994). The Syndication of Venture Capital Investments. *Financial Management*, 23(3):16–27.
- Lerner, J. (1995). Venture Capitalists and the Oversight of Private Firms. *The Journal of Finance*, 50(1):301–18.
- Levine, R. and Rubinstein, Y. (2017). Smart and illicit: Who becomes an entrepreneur and do they earn more? *The Quarterly Journal of Economics*, 132(2):963–1018.
- Liberti, J. M. and Petersen, M. A. (2018). Information: Hard and soft. *The Review of Corporate Finance Studies*, 8(1):1–41.
- Manso, G. (2011). Motivating innovation. *The Journal of Finance*, 66(5):1823–1860.
- Manso, G. (2016). Experimentation and the returns to entrepreneurship. *The Review of Financial Studies*, 29(9):2319–2340.
- Moore, D. A. and Healy, P. J. (2008). The trouble with overconfidence. *Psychological review*, 115(2):502.
- Moskowitz, T. J. and Vissing-Jørgensen, A. (2002). The returns to entrepreneurial investment: A private equity premium puzzle? *American Economic Review*, 92(4):745–778.
- Musto, D. K. (2004). What happens when information leaves a market? evidence from post-bankruptcy consumers. *The Journal of Business*, 77(4):725–748.
- Nahata, R. (2008). Venture capital reputation and investment performance. *Journal of financial economics*, 90(2):127–151.
- Nahata, R. (2019). Success is good but failure is not so bad either: Serial entrepreneurs and venture capital contracting. *Journal of Corporate Finance*, 58:624–649.
- Nanda, R. and Rhodes-Kropf, M. (2017). Innovation policies. In *Entrepreneurship, Innovation, and Platforms*, pages 37–80. Emerald Publishing Limited.
- Peng, M. W., Yamakawa, Y., and Lee, S.-H. (2010). Bankruptcy laws and entrepreneur-friendliness. *Entrepreneurship theory and practice*, 34(3):517–530.
- Petersen, M. A. and Rajan, R. G. (2002). Does distance still matter? The information revolution in small business lending. *The Journal of Finance*, 57(6):2533–2570.
- Puri, M. and Robinson, D. (2007). Optimism and economic choice. *Journal of Financial Economics*, 86(1):71 – 99.
- Puri, M. and Robinson, D. (2013). The economic psychology of entrepreneurship and family business. *Journal of Economics Management Strategy*, 22(2):423–444.
- Puri, M. and Zarutskie, R. (2012). On the life cycle dynamics of venture-capital- and non-venture-capital-financed firms. *The Journal of Finance*, 67(6):2247–2293.

- Retterath, A. and Braun, R. (2020). Benchmarking venture capital databases. *Working Paper*.
- Robb, A. M. and Robinson, D. (2014). The capital structure decisions of new firms. *Review of Financial Studies*, 27(1):153–179.
- Rodano, G., Serrano-Velarde, N., and Tarantino, E. (2016). Bankruptcy law and bank financing. *Journal of Financial Economics*, 120(2):363–382.
- Sahlman, W. (2010). Risk and reward in venture capital. *Harvard Business School Note*, 811.
- Samila, S. and Sorenson, O. (2011). Venture capital, entrepreneurship, and economic growth. *The Review of Economics and Statistics*, 93(1):338–349.
- Schumpeter, J. (1942). Creative destruction. *Capitalism, socialism and democracy*, 825:82–85.
- Shane, S. and Cable, D. (2002). Network ties, reputation, and the financing of new ventures. *Management Science*, 48(3):364–381.
- Simmons, S. A., Wiklund, J., and Levie, J. (2014). Stigma and business failure: implications for entrepreneurs' career choices. *Small Business Economics*, 42(3):485–505.
- Sorenson, O. and Stuart, T. E. (2001). Syndication networks and the spatial distribution of venture capital investments. *American Journal of Sociology*, 106(6):1546–1588.
- Sorenson, O. and Stuart, T. E. (2008). Bringing the context back in: Settings and the search for syndicate partners in venture capital investment networks. *Administrative Science Quarterly*, 53(2):266–294.
- Stein, J. C. (2002). Information production and capital allocation: Decentralized versus hierarchical firms. *The Journal of Finance*, 57(5):1891–1921.
- Sørensen, M. (2007). How smart is smart money? a two-sided matching model of venture capital. *The Journal of Finance*, 62(6):2725–2762.
- Tian, X. (2011). The Role of Venture Capital Syndication in Value Creation for Entrepreneurial Firms. *Review of Finance*, 16(1):245–283.
- Tian, X. and Wang, T. Y. (2014). Tolerance for failure and corporate innovation. *The Review of Financial Studies*, 27(1):211–255.
- Townsend, D. M., Busenitz, L. W., and Arthurs, J. D. (2010). To start or not to start: Outcome and ability expectations in the decision to start a new venture. *Journal of Business Venturing*, 25(2):192–202.
- Wasserman, N. (2008). The founder's dilemma. *Harvard business review*, 86:102–9, 138.
- Weinstein, N. D. (1980). Unrealistic optimism about future life events. *Journal of Personality and Social Psychology*, 39(5):806–820.

- Xu, T. (2018). Learning from the crowd: The feedback value of crowdfunding. *Working Paper*.
- Zhang, L., Gupta, A. K., and Hallen, B. L. (2017). The Conditional Importance of Prior Ties: A Group-Level Analysis of Venture Capital Syndication. *Academy of Management Journal*, 60(4):1360–1386.

RÉSUMÉ

Cette thèse offre un nouvel aperçu de l'entrepreneuriat en série et du financement par capital-risque. Le premier chapitre porte sur les capital-risqueurs et leur processus de sélection. Il décrit comment ces derniers ont géré un choc qui a profondément marqué leur modèle d'investissement traditionnel. Contraints de remplacer les interactions en personne, considérées comme essentielles pour la collecte de soft information, par des réunions en ligne, ils ont évolué vers un nouveau modèle d'investissement. Le deuxième et le troisième chapitre se concentrent sur la perception des expériences par les investisseurs. Le deuxième réunit la notion de stigma et les biais entrepreneuriaux dans un cadre théorique. Il suggère que la surconfiance joue un rôle significatif pour éviter la stigmatisation de l'échec mais pas l'optimisme. Le troisième chapitre montre qu'à l'inverse des idées reçues, toute expérience n'est pas toujours valorisée aux États-Unis. Il révèle les conditions sous lesquelles les capital-risqueurs stigmatiseraient l'échec.

MOTS CLÉS

Entrepreneuriat, Capital-Risque, Biais Comportementaux, Experimentation, Stigma.

ABSTRACT

This thesis provides new insights into serial entrepreneurship and venture capital financing. The first chapter concentrates on venture capitalists and their selection process. It describes how these latter handled a shock that profoundly stressed their traditional investment model. Being forced to replace in-person interactions, considered essential for soft information collection, with online meetings, they have made some steps toward a new investment model. The second and third chapters focus on investors' perceptions of past founder experience. The second combines the notion of stigma and well-documented entrepreneurial biases in a theoretical framework. It suggests that overconfidence has a meaningful role in avoiding the stigma of failure and highlights that this is not true for optimism. The third chapter shows that, as opposed to common priors, all experiences are not always celebrated in the US. It especially reveals conditions under which venture capitalists might stigmatize failure.

KEYWORDS

Entrepreneurship, Venture Capital, Behavioral Biases, Experimentation, Stigma.

