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The Impact of Busyness on Venture Capital Screening

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Abstract

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Keywords: Venture Capital, VC, Distraction, Industry Shock, Screening, Pre-Investment Screening, MOIC, Panel Data

Purpose: The main purpose of the thesis is to understand whether venture capitalists are able to select ventures with an ex-ante higher likelihood of success. To impose variation to VCs' ability to select the right ventures, we use industry shocks as a measure of distraction.

Theoretical Framework: Pre-investment screening, deal sourcing, investment sorting process, due diligence, term sheet, screening criteria, syndication, monitoring, exit.

Methodology: This thesis will use a quantitative research approach using fixed effect regression analysis of a panel data set. We use two dependent variables in the form of an exit multiple (*MOIC)* and an exit dummy. Several controls will be used, and robustness tests will be implemented.

Empirical Foundation: The final sample consists of 45,772 investment observations from 87 quarters. Both the VC firms and the portfolio companies are from the US. The investment and exit data was retrieved from Refinitiv Eikon and the industry returns were retrieved from Wharton Research Data Services.

Conclusion: We find that distraction induced by industry shocks and moderated in impact by the weight of the affected portfolio, is not sufficiently pronounced to impact portfolio company outcomes. To validate our results, we exploit heterogeneity in the treatment intensity by introducing variables that reinforce busyness and the impact of the industry shock. We find that busyness is especially severe when VC funds predominantly engage in lead investments. However, we find no evidence to support the notion that syndication, as a means to distribute additional advice across co-investors, mitigates busyness.

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1. Introduction

1.1 Background

Venture capital (VC) is a large market and has managed to handle the Covid-19 pandemic impressively (Hyder, 2021). Even though 2020 was a difficult year for many corporations, American companies managed to raise $148 billion from venture capital firms (Hyder, 2021). The VC-market has become an integral part of the business sphere but recently there have been new ways of finding funding for young companies. Many new online crowdfunding websites have become increasingly impactful (Puskoor, 2020). Since new methods of finding capital for young companies have become more impactful, the relevance of the VC is being challenged. Further, because of this must VC firms ensure their superior ability in generating value through both pre- and post-investment activities.

VC financing has been crucial to the emergence of innovative companies. Ever VC-backed companies account for 44% of the research and development spending and one-fifth of the market capitalization of US public companies (Gornall and Strebulaev, 2015). Notable examples include Facebook, Amazon, Apple, Netflix, and Google (Gompers et al., 2020). Kaplan and Lerner (2010) estimate that as many as 50% of all initial public offerings (IPOs) have been backed by a VC whilst only about 1% of all companies have ever been supported by VCs. In the same vein, Kaplan and Schoar (2005) find persistence in the significant returns generated by VCs that on average outperform public markets net of fees (Harris, Jenkinson, and Kaplan, 2016). The favorable outcomes for VC-backed companies are in line with the general belief that VCs help companies create value (Gompers et al., 2020). The question then arises how VCs create value. Do VCs create value solely by contributing to the development of ventures by post-investment monitoring using their networks and reputation, i.e., “monitoring”? Or are VCs able to select those firms ex-ante that they know will succeed in the future, i.e., “screening”? Our research paper will seek to answer the latter question.

A venture capitalist (VC) is a financial intermediary that invests external capital into private companies and engages actively in post-investment value-adding activities to maximize the return on investment upon exit, often from an early stage of the company’s life cycle (Metrick and Yasuda, 2010, p. 3). The active role post-investment includes monitoring activities and the provision of advice which we will refer to as “monitoring”, as well as contracting (Gompers et al., 2020). 27% of VCs self-report that monitoring is the most important factor in value creation, while screening is considered by 49% to be the most crucial. The screening process often takes hundreds of possible investments and narrows them down to just one (Metrick and Yasuda, 2010, p. 136).

VC activities have been a topic of much discussion in the literature (see e.g., Kaplan and Strömberg, 2000; Kaplan and Strömberg, 2001; Gompers et al., 2020). Gompers et al., (2020) for instance used a survey in order to document how VCs make decisions. Similarly, Kaplan and Strömberg (2000) analyzed 10 VC firms and 42 portfolio companies to research how VCs make their initial investment decisions. While screening is considered by VCs to be the primary value driver in their success, little attention has been given to the empirical quantification of the impact of screening. The problem in such a quantification arises from the disentanglement of screening and monitoring (Sørensen, 2006) and the inability to observe VC involvement (Abuzov, 2020).

1.2 Problem Definition and Relevance

The persistence in significant returns realized by VCs and considerable share of VC-backed ventures among true IPOs is consistent with the notion that VCs engage in activities that generate value (Gompers et al., 2020). Kaplan and Strömberg (2001) highlight, in particular, VCs' skill in pre-investment screening of potentially successful ventures, complex contracting and post-investment monitoring. The fundamental problem in the empirical quantification of the impact of VC screening as an isolated activity arises from the interrelatedness of these activities and the requirement, in particular, to disentangle screening from monitoring; that is, since measured ex-post outcomes invariably include the treatment effect of monitoring. An experiment to eliminate the treatment effect and capture at least part of the impact of screening would be to compare future outcomes of ventures that have undergone the due diligence process but have been rejected, with future outcomes of a set of random companies. However, information on screened yet rejected companies does not, to the best of our knowledge, exist in any publicly available database. On the other hand, comparing outcomes of VC-backed and non-VC-backed companies ex-ante would disregard unobservable firm characteristics, such as the skill of the entrepreneur, that contribute to ex-post performance. Another useful experiment would be to vary the level of involvement in the screening process but to leave the level of monitoring involvement unchanged. This approach is analogous to Bernstein, Giroud, and Townsend (2016) who exploit exogeneous variation in monitoring involvement arising from travel time reductions. Screening thereby remains fixed. Screening involvement on its own account is, however, difficult to observe as Abuzov (2020) notes. To introduce variation to the otherwise unobservable involvement in screening could warrant the application of factors that induce busyness to the economic agent. Similar to Bernstein, Giroud, and Townsend (2016) who consider travel time reductions, Bennedsen, Pérez-González and Wolfenzon (2020) who consider hospitalizations and Stein and Zhao (2016) who use poor stock performance of directors' employers, Abuzov (2020) introduces a measure of distraction using the 3-5-month lasting active IPO process that requires careful navigation of VCs to achieve high multiples. Although not mentioned in his paper, Abuzov (2020) thereby makes the implicit assumption that no economically meaningful variation is imposed on the level of monitoring involvement – or at least not such an extent so as to affect portfolio company outcomes. This is arguably true because the added value of monitoring is spread across the entire life-cycle of the venture, while screening is a time-limited process that lasts just one quarter. To corroborate Abuzov's (2020) results and minimize the potential endogeneity of monitoring involvement, an event horizon, shorter than the active IPO phase, could be employed. In this paper, we argue that an industry shock to parts of a VCs' portfolio represents a valid alternative which at the same time limits distraction to just one quarter.

There are many different methods of collecting funds today (Puskoor, 2020) with institutional investors, such as pension funds, increasingly ramping up plans to create their own private equity investment programs (Cumming, 2019). It is therefore increasingly important to establish the impact and skill of a VC firm to predict positive outcomes in order to show their ability to create value for investors.

1.3 Aim and Purpose

This paper aims to give further substance to the discussion surrounding where a VC creates value, more specifically how valuable the pre-investment screening is. To do this we will try and isolate the influence of the pre-investment screening process by exploiting exogenous variation in screening involvement arising from an industry shock. Further, as an industry shock which affects limited parts of the VCs activities, most prominently the monitoring of the firms affected by the shock, it should lead to less time being spent on other activities such as the screening process. By using exit multiples in the form of a multiple on invested capital (*MOIC*) (see Section 4.2.2) as the main dependent variable we will observe the differences in the performance from investments done when the VCs are ‘busy’. Moreover, we will also observe the probability of a portfolio firm going public or being acquired when the VCs are distracted in comparison to non-distracted investments. By using different controls and robustness tests we intend to create a robust and reliable model. This method could help determine the quantitative importance of this process which is not yet established. It could be useful for practitioners within venture capital including entrepreneurs searching for capital and for VCs. For entrepreneurs it could be useful with the purpose of understanding how effective VCs are in choosing the best investment in contrast to creating value post investment i.e., it could give them more knowledge about the importance of their venture before the search for a VC even begins. For VCs it could be further evidence of their importance in relation to the changing environment described by Puskoor (2020) and their method of choosing the best available investment through their knowledge about deal sourcing, the due diligence process, syndication as well as their experience could become more entrenched. To conclude, the purpose of this paper is to give practitioners such as VCs and entrepreneurs a clearer image of how important, in quantitative terms, the screening process is. This paper will hopefully further enrich the literature about venture capital and the value of the activities within it.

1.4 Research Question

The problem definition and purpose will culminate into the following research question:

Are investments made by busy VC firms less likely to go public and/or do they have a lower exit multiple?

1.5 Disposition

The disposition of this paper will be structured as follows. In section 2 we will discuss the theoretical framework of this thesis. Further, a discussion about what venture capitalists do with focus on the initial screening process as well as a discussion regarding time constraints will be included. These topics will help determine the structure of our empirical model. Section 3 gives insights on previous research on the topic of discussion followed by the hypotheses of the paper. Section 4 will present our methodology approach, the empirical model as well as a discussion about the data and the descriptive statistics. In section 5 we will showcase our results and analyze them. Lastly, section 6 will include our concluding remarks where we discuss the main findings of our results. This will be followed by a discussion about the limitations of the paper and possible further research.

2. Theory

We start the theoretical part of the paper by defining the venture capitalist (VC). Throughout the study we will use VC interchangeably with VC firm, VC fund and VC partner and specify the specific hierarchy where necessary. We will continue with a detailed description of VC activities, including screening, monitoring, and exit and conclude with the concept of time scarcity in venture capital.

2.1 The Venture Capitalist

A venture capitalist (VC) is a financial intermediary that invests external capital into private companies and engages actively in post-investment value-adding activities to maximize the return on investment upon exit (Metrick and Yasuda, 2010, p. 3). VC firms are typically small organizations, comprising on average about 10 professionals who serve as general partners (GP) for the VC fund. VC funds are structured as finite investment vehicles and can be specialized by industry, stage, or geography, investing on behalf of the investors ("the limited partners or LPs"). LPs are primarily institutional investors that promise to provide a certain amount of capital over the lifetime of the fund. To compensate the VCs, LPs pay a set percentage on the committed capital as well as carried interest on the profits of the fund (Metrick and Yasuda, 2010, p. 3). The VC engages in three primary activities: pre-investing screening, monitoring and exit (Kaplan and Strömberg, 2001).

2.2 What Do Venture Capitalists Do?

Much of the theory presented in this section is drawn from the large-scale survey conducted by Gompers et al. (2020) who provide an unprecedented level of detail into the workings of venture capitalists. The general framework of VC activities is based on Kaplan and Strömberg (2001).

2.2.1 Pre-Investment Screening and Selection

Venture capitalists invest in projects with short operating and financial histories, pro-longed unprofitability, technologically complex products, and a business environment with a range of legal and technical uncertainties (e.g., Yung, 2012). To evaluate the quality of an investment opportunity, external financiers will therefore engage in extensive pre-investment screening. The pre-investment screening, which we will refer to as "screening", performed by VCs, is a multi-stage process: VCs source ("deal sourcing"), sort through ("investment selection process”), and conduct due-diligence on investment opportunities. Venture capitalists finalize the conditions of the financing in a term sheet. Entrepreneurs can agree to the conditions using a letter of commitment thereby closing the deal (Gompers et al., 2020).

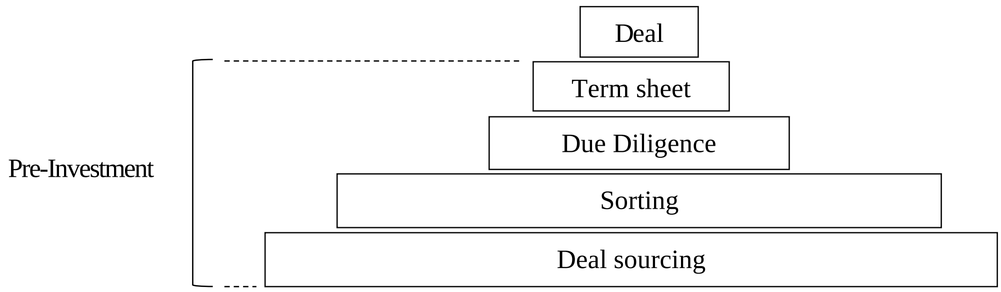


Figure 1: The Pre-Investment Process

The degree to which venture capital firms use a formal process during pre-investment screening is related to the size of the firm. While in small firms, investment sorting, due diligence, and the decision to invest tends to be a joint process by all partners of the firm, midsize firms with more than five partners will designate a “lead partner” who prepares either a memo or presentation that precedes the partnership investment. Unlike small and midsize firms, large firms will employ more junior partners and associates for the purpose of investment sorting and due diligence. Investment decisions will be made by a committee of senior partners (Metrick and Yasuda, 2010, p. 136).

Deal sourcing

Much of the VC’s investment opportunities are generated either proactively (30%), by other investors (28%) or through professional networks (30%) while inbound requests by entrepreneurs comprise just 10% of all deals (Gompers et al., 2020). The amount of possible high-quality investments is dependent on the sourcing strategy and the reputation of the VC, with higher reputation firms having to devote less time to find good investments (Metrick and Yasuda, 2010, p. 137). To sort through investment opportunities, VCs use a multi-stage process.

Investment sorting process

Investment opportunities are first screened by the individual originator (e.g., a senior partner, an associate, a venture partner) using a set of screening criteria (see section ”Screening Criteria”) related to the business (“the horse”). If the investment appears promising, the individual originator will meet the company management (“the jockey”), confirming his/her perception in a second review with the support of other partners at the venture capital firm. At each of these stages, a significant number of investments are eliminated. One in four investment opportunities leads to a meeting with the portfolio company management, and one third of those are reviewed at a partners meeting. Half of the projects reviewed at the partners meeting will proceed to the due diligence process. Large VC firms tend to employ more junior partners and associates conducting more management meetings and a lengthier due diligence process (Gompers et al., 2020).

Due diligence

Once potential investments have been scrutinized, VC partners engage in a more formal due diligence process that entails e.g., peer comparisons, calling references, and/or industry analyses. VCs devote considerable time to this process averaging 118 hours per deal, with a shorter horizon for early-stage and healthcare companies (Gompers et al., 2020).

Term sheet and deal

Roughly a third of the investment opportunities that have been subject to due diligence, will be made a preliminary offer with a term sheet expressing the interest of the VC to invest in the portfolio company (Metrick and Yasuda, 2010, p. 146). The portfolio company can either accept, reject, or re-negotiate the term sheet. The average venture capitalist will offer 1.7 term sheets per closed deal since multiple VCs compete for a single investment opportunity (Gompers et al., 2020). To close one deal, the median VC screens roughly 100 investment opportunities, closing four deals per year. The number of firms screened differs in respect to industry. The hypothesis is that certain industries require greater domain specific knowledge, and with greater fixed costs incurred, in equilibrium, less firms will be screened (Gompers et al., 2020).

Screening criteria

Kaplan, Sensoy and Strömberg (2009) developed the “jockey vs. horse” framework categorizing screening criteria as either the “horse”, i.e., the market, the technology, the customers, the competitors, financial projections, and exit strategies - in short factors related to the business – or the “jockey”, i.e., the management and/or the entrepreneur of the portfolio company. VCs will seek out novel products with sustainable competitive advantage and technological superiority in large markets with high portfolio momentum (Metrick and Yasuda, 2010, p. 16). They further look for able, experienced, and passionate entrepreneurs (Gompers et al., 2020). To translate qualitative factors into valuations, VCs employ earnings, sales, and EBIT forecasts (Kaplan and Strömberg, 2000). In the large-scale survey by Gompers et al. (2020), 95% of VC firms consider the jockey to be important - 47% the most important factor - while 83% perceive the horse to be important - 37% the most important factor. Meaningful cross-variation persists across industries and stages, with later-stage investments placing more emphasis on business-related factors (Gompers et al., 2020).

The pre-investment screening process and market conditions

Knowledge acquisition by VCs can be transferable across ventures, e.g., knowledge of a particular technology and its potential to impact a market. Pre-investment screening can therefore be considered to have option value where improving market conditions, and associated therewith, a greater number of attractive investment opportunities increase the option value (Yung, 2012). Market conditions therefore affect venture capitalists' portfolio holdings and returns; good market conditions lead to a substitution towards late-stage investments (Cumming, Fleming and Schweinbacher, 2005), higher realized returns and larger portfolios (Cumming 2006; Kannianen and Keuschnigg, 2003) while bad market conditions lead to the respective opposite. Yung (2012) argues that larger VC portfolios exacerbate VCs' time constraints with less time spent on each portfolio company. Since late-stage investments require less time - early-stage investments more time - Yung (2012) posits that VCs re-deploy resources in the face of changing market conditions.

Syndication

Venture capitalists mainly invest as a syndicate (Lerner, 1994), one the one hand, due to reasons related to portfolio theory, and on the other hand, as a positive signal for entrepreneur firms (Yung, 2012). Because VCs' are time- and capacity-constrained in their ability to engage in screening and monitoring, they are inherently undiversified; syndication thus serves to diversify some of the idiosyncratic risk. Syndicated investments are further associated with higher valuations, and a higher probability of exit via IPO and thereby act as positive signals (Tian, 2012).

2.2.2 Monitoring

Venture capitalists monitor portfolio companies for two reasons: on the one hand, to alleviate the agency cost of the separation of ownership and control and, on the other hand, to add value by serving as an input to the firm's development. In receiving a portion of future profits, VCs are quasi-owners of the portfolio company (Sahlman, 1990); the separation of ownership and control thus gives rise to agency risk, i.e., opportunistic, or self-serving behavior by the entrepreneur or manager. Governance and explicit monitoring activities, e.g., scrutinizing management, employing incentive compensation structures (see Hellmann and Puri, 2000), therefore serve as mechanisms to align the interests of the VC with those of the portfolio company (e.g., Jääskeläinen, Maula, and Seppä, 2006). To improve portfolio company outcomes and mitigate information asymmetry, VCs sit on boards, hire outside managers - and directors - connect to investors and customers and provide guidance on strategic and operational matters (Gompers et al., 2020). In light of the range of activities performed by VCs, it is not surprising that 60% of VCs interact at least once per week with their portfolio companies. The level of involvement does not differ fundamentally by investment stage; arguably because certain activities are more relevant for certain investment stages, e.g., connecting to investors in early-stage investments and strategic and/or operational guidance in later-stage investments. The majority of VCs provide strategic guidance (87%), presumably as part of their board member/observer role (Gompers et al., 2020). 44% of VCs in fact serve as members of the board; with a progressively higher probability for lead-investors of independent venture capital firms in early-rounds (Amornsiripanitch, Gompers and Xuan, 2019). 58% of VCs hire board members, 46% hire employees with meaningful cross-sectional variation across industry and investment stage, respectively. VCs use their internal network to connect portfolio companies to customers (69%) and investors (72%) and provide operational guidance in 65% of cases. In light of the day-to-day involvement in operations and strategy, Gompers et al. (2020) argue that VCs should be viewed as active investors exerting costly effort, adding value to their portfolio companies.

2.2.3 The Exit

Because VC funds are typically structured as finite investment vehicles that realize gains only when the invested capital is returned to external investors, the type and timing of exit is crucial to the VC (Gompers et al., 2020). VCs self-report that 15% of exits are through an IPO, 53% are through M&A, and 32% are failures (i.e., liquidation of the company). An exit is thus considered successful when it is realized as an IPO or M&A, with M&A arguably being more lucrative (Metrick and Yasuda, 2010, p. 179). However, with M&As potentially being disguised failures (see Gompers et al., 2020), *MOIC* as a measure of VC success may be a more accurate representation.

2.3 VC Time Constraints

The survey by Gompers et al. (2020) demonstrates that venture capitalists expend a significant amount of time and effort on pre-investment screening and monitoring activities. In this light, Kaplan and Strömberg (2001) argue that time, not capital is the scarcest resource of venture capitalists. Yung (2012) similarly hypothesizes that physical time constraints induce VCs to substitute toward later-stage investments in the face of improving market conditions since those are, given a pro-longed financial history, generally easier to evaluate. Conversely, substitution toward early-stage investments in the face of deteriorating market conditions, appears to be a mechanism to fully deploy VC attention since early-stage investments generally require greater knowledge of technology and development timelines (see Gompers et al., 2020). Venture capitalists' attention is thus not unbounded, but optimally allocated so that the performance of the portfolio is maximized (see Jääskeläinen, Maula, and Seppä, 2006).

Busyness, in the framework of the portfolio of VC investments, however, does not have to be value-destructive: Jääskeläinen, Maula, and Seppä (2006) show that there is an inverted U-shaped relationship between venture capitalists' allocation of attention to investments and the performance of their portfolios. The value of busyness, in connection with a progressively larger portfolio of companies per VC, arises from the diminishing return on VC involvement per venture. The marginal return can turn zero or negative when the VCs' value-contributing knowledge base is exhausted and/or if the venture capitalist engages in too much monitoring. At this point, it would be better for the VC to spread his/her involvement across more ventures. Busyness can be value-destructive on the individual investment level when the return on involvement is positive - on the portfolio level – when the value of busyness falls below the overhead cost (e.g., travel time to visit the portfolio company). The relationship between the portfolio size and the return on busyness in turn is moderated by syndication (Jääskeläinen, Maula, and Seppä, 2006). When busyness is value destructive, i.e., when the return on involvement is positive, VCs are attention- and time-constrained. An increasing portfolio size will cause busyness to be value-destructive since - when marginal return on involvement is positive – advice is spread out too thinly to achieve optimal results. Syndication mitigates the attention dilemma given that the additionally required advice can be picked up by co-investors. Whilst syndication thereby enables co-investors to reduce their commitment and managerial resources, much of the management of the investment is delegated to the lead investor (Gorman and Sahlman, 1989; Wright and Lockett, 2003). In fact, Gorman and Sahlman (1989) find that lead investors interact 10 time as much with ventures. The workload is furthermore increased by the administrative management of the syndicated investment (Wright, and Lockett, 2003). Time constraints are therefore mitigated through syndication and exacerbated for the lead investors.

3. Review of Previous Research on the Effect of Venture Capital Screening

While the body of research documenting how venture capitalists select and monitor portfolio companies (e.g., Gompers et al., 2020; Kaplan and Strömberg, 2000) is well developed, empirical research on whether VC screening is valuable in the sense that exit outcomes can be predicted by venture capitalists, is scant.

3.1 VC Screening in the Literature

Much of the empirical literature studying the effect of VCs on portfolio company outcomes, compares the outcomes of VC-backed portfolio companies with non-VC-backed firms (e.g., Hellmann and Puri, 2002; Chemmanur, Krishnan, and Nandy, 2011; Puri and Zarutskie, 2012). In this context, the selection of investments by VCs ("screening") is only addressed as the selection bias in the estimation of the treatment effect of VC financing. The selection bias arises from venture capitalists' competitive advantage in selecting better investments along a series of factors that are unobservable in the data. The likelihood that VC-backed firms are better investments ex-ante and perform better ex-post, even absent of VC involvement, is therefore greater (Dessi and Yin, 2012). Unobservable firm characteristics in the error term are thus related to portfolio company outcomes and correlated with the treatment dummy variable. Most of the literature on VCs and company outcomes, therefore, aims to control for the upward bias arising from the investment selection but disregards to estimate its effect. Notable exceptions are Chemmanur, Krishnan, and Nandy (2011) and Croce, Marti and Murtinu (2013) who assign productivity differences ex-ante of VC and non-VC-backed firms to the effect of VC screening. Croce, Marti and Murtinu (2013) in fact equate the lack in differences in productivity prior to investment with a general independence of final productivity outcomes to VCs' screening activity. VCs, however, indicate the significance of unobservable screening criteria (e.g., the intrinsic abilities of the entrepreneur) and Sørensen (2006) finds that unobserved sorting contributes more to final outcomes than observed sorting. Observable firm characteristics therefore only take a minor part in future company outcomes.

Analogous to the literature comparing VC and non-VC-backed firms, to document to the effect of VC screening, one could compare company outcomes of VC firms that 'almost' received funding, i.e., those firms that have undergone the due diligence process but have been ultimately rejected, with non-VC-backed firms. While Fried and Hisrich (1994) highlight that the due diligence process is rigorous, time and attention constraints and unresolved questions can cause venture capitalists to reject business proposals that were in fact considered solid (Boocock and Woods, 1997). A case study by Steier and Greenwood (1995) accordingly finds that venture capitalists often revisit past decisions. A comparison of screened yet rejected firms and non-VC backed firms would therefore capture the effect of deal sourcing and, at least to an extent, the effect of the investment sorting process while holding monitoring involvement constant. The methodological design would resemble that of a regression discontinuity design. However, to the best knowledge of the authors, information on screened non-VC funded firms does not exist in any commercial database. A survey by Rin, Hellmann, and Puri (2013) on venture capital research corroborates the lack of data on firms that did not receive VC financing.

The first research to estimate the relative importance of screening and monitoring on company outcomes was conducted by Sørensen (2006) who hypothesized a positive relationship between the experience of a VC (i.e., the number of investments undertaken) and his/her ability to sort ("screen") *and* influence ("monitor") portfolio companies. To solve the related endogeneity problem arising from the correlation between investors' experience and the unobserved investment characteristics in the error term that positively contribute to investment outcomes, Sørensen (2006) exploits an exogenous property of the market's sorting mechanism: VC investments are the outcome of a two-way sorting mechanism where better companies select more experienced VCs (Hsu, 2004), *and* more experienced VCs select better companies. This means that in a market with less experienced VCs, an experienced investor could expect improved deal flow and ultimately better company selection. The investment VC-to-company match is therefore dependent on, and the investment outcome independent of, the experience of other VCs in the market. Using a structural model, Sørensen (2006) exploits this exogenous variation in sorting, to disentangle the effect of influence and sorting. He finds that investors' influence accounts for one-third, sorting for two-thirds of the percent-increase in the likelihood of an IPO. Unlike Sørensen (2006), Bernstein, Giroud, and Townsend (2016) document the impact of monitoring - Abuzov (2020) documents the impact of screening - without having to rely on structural assumptions.

3.2 The Impact of VC Screening

Abuzov (2020) thereby exploits an exogenous shock to VCs' attention. As a measure of distraction, he uses IPOs of firms unrelated to the investment but related to the VC, to document differences in exit multiples and the likelihood of an IPO or acquisition between investments undertaken by 'distracted' and 'non-distracted' VC partners. Akin to Kempf, Manconi and Spalt (2017) who study the impact of distracted shareholders on corporate actions, and Stein and Zhao (2016) who determine the adverse effects of director distraction, Abuzov (2020) supposes that economic agents are bounded in their attention, such that temporary shocks to an unrelated, but to the economic agent relevant, activity shifts attention away from the activity of interest. The underlying idea is that if the screening involvement, performed by the economic agent, had no effect on VCs' ability to pick winners, then an attention-grabbing shock would have, all else being equal, no impact on the outcome of the investment. By supposing a shift in attention from the screening activity to the engagement in IPOs, Abuzov (2020) introduces variation to the otherwise unobservable involvement of VCs during screening. He finds that investments made by 'distracted' VC partners have lower exit multiples and are 7% less likely to get acquired or become public. The adverse effects of distraction hold for VC funds, however, fail to substantiate in VC firms, arguably because of the aggregation of 'distracted' and 'non-distracted' VC partners. A problem not discussed by Abuzov (2020) relates to the disentanglement of VC screening and VC monitoring, i.e., he assumes that the active engagement in the IPO process by VC partners does not compromise their ability to monitor portfolio companies post investment or at least not to such an extent so as to affect the outcome of investments undertaken by 'distracted' VC partners. If the added value of monitoring involvement were spread equally across time, it could be argued that the distraction event affects monitoring to a lesser degree, since an investment takes, on average, only 83 days to close while monitoring involvement follows the entire venture lifecycle (see Gompers et al., 2020). Using efficiency gains as an outcome variable of the impact of monitoring involvement by VCs, Chemmanur, Krishnan, and Nandy (2011), however, find that efficiency gains are investment round-dependent, increasing monotonically from round 1 to the end of round 2, significantly from round 2 to round 3, and stagnating thereafter. The added value of monitoring is therefore presumably concentrated around the first investment rounds, which means that the impact of the distraction event on company outcomes, given compromised screening, may not be independent of the effect of monitoring, since, arguably, some level of economically meaningful variation is imposed on monitoring involvement. To document the effect of the distraction event on outcomes, Abuzov (2020) holds the investment rounds fixed; a more meaningful model would however relate the company outcome to a distraction event, conditional on the investment round (i.e., an interaction term). To minimize the potential impact of the endogeneity of monitoring, an event horizon, shorter than the 3-5 month lasting active IPO phase, would furthermore make the results more convincing.

3.3 Use of Distraction Events in the Literature

Using time-varying distraction/attention-grabbing events as a methodological design to introduce exogenous variation to the involvement of economic agents is a common theme in the literature. Kempf, Manconi and Spalt (2017) use industry shocks to unrelated parts of an investor's portfolio as a measure of distraction in order to analyze whether this distraction has any implications on corporate actions. Their assumption is that the monitoring capacity supplied by investors is a scarce resource whose allocation is based on a tradeoff between benefits and costs. A temporary positive or negative shock to parts of the portfolio would induce monitors to shift attention in an effort to equate the marginal benefit across firms in the portfolio. Following the notion that it is more valuable for portfolio managers to shift attention to more uncertain outcomes (e.g., Kacperczyk, Nieuwerburgh, and Veldkamp, 2016); Kempf, Manconi and Spalt (2017) use cross-sectional extreme positive and negative industry returns, moderated in impact by the weight of the shocked-industry in the portfolio holdings, as a proxy for distraction. In the same vein, Stein and Zhao (2019) use poor stock performance of directors' employers as a distraction to directors' roles on boards on unrelated firms to measure the effect on earnings quality and M&A performance.

3.4 Hypothesis Development

Venture capitalists invest in projects with short operating and financial histories, pro-longed unprofitability, technologically complex products, and a business environment with a range of legal and technical uncertainties. As a result, VCs expend significant time and resources to screen through the potentially most successful candidates. In the same vein, VCs self-report that the screening process is the most important factor in value creation (Gompers et al., 2020). Concurrently, 50% of IPOs are VC-backed despite only 1% of ventures having received financing by VCs (Kaplan and Lerner 2010). Thus, since VCs likely self-select activities that are value-contributing, it stands to reason that besides adding value by monitoring ventures, VCs are in fact able to select those ventures that are poised to succeed. Time, on the other hand, is VCs' scarcest resource. VCs engage in activities that maximize the return of their portfolio (Jääskeläinen, Maula, and Seppä, 2006) and thereby allocate their involvement *or* attention both across ventures and activities. In this framework of optimal allocation of attention, we expect that temporary increments in the supply of monitoring to certain ventures will reduce the supply of attention to unrelated ventures (see Kempf, Manconi and Spalt, 2017).

As active investors, VCs hire outside managers - and directors - connect ventures to investors and customers and provide guidance on strategic and operational matters (Gompers et al., 2020). VCs' involvement does not change across the investment stage which means that their monitoring involvement remains unaffected along the entire lifecycle (see Gompers et al., 2020). To select investment opportunities, VCs engage in a time-consuming multi-stage sorting process that begins with roughly 100 opportunities and concludes in a single investment with the average deal taking 83 days to close. Although added value by VCs' monitoring is likely concentrated at the first rounds of investment (see Chemmanur, Krishnan, and Nandy, 2011), fundamental differences, between screening and monitoring, in the distribution of the added value across time arguably cause temporary changes in attention to affect outcomes related to screening to a greater extent. We therefore expect that temporary increases in monitoring involvement to some ventures adversely affect, in particular, *screening* supply to potential unrelated ventures. If VCs in fact had no ability to select successful investment opportunities, provided that attention was allocated optimally ex-ante, then temporary increases in the monitoring involvement to certain ventures should have no influence on portfolio company outcomes of unrelated ventures. Our main hypothesis therefore is that distraction *or* busyness on the VC firm-level compromises VCs screening. In particular, we expect less informed decisions (see Chen and Guay, 2020), inaccurate valuations and/or insufficient due diligence causing such "busy investments" to perform worse, all else being equal. Changes in monitoring involvement, however, must be exogenous. Adverse market conditions for example compromise the intrinsic quality of ventures, i.e., presumably impairing venture outcomes, while inducing an increase in screening supply as a mechanism to redeploy idle resources (see Yung, 2009; Yung, 2012). In this example, increased screening involvement *causes* venture outcomes to decrease, not increase.

Hypothesis 1: Investments that have been made concurrently with exogenous increases in monitoring involvement in unrelated ventures perform worse than those unaffected.

If the adverse effect of temporary increments in the monitoring supply are indeed attributable to the effect of busyness, we expect the effect to be greater (smaller) for VCs that are more (less) time-constrained. In this light, syndication plays a fundamental role in mitigating attention constraints to co-investors since VCs distribute advice across syndicate partners and thereby reduce commitment and managerial resources (Jääskeläinen, Maula, and Seppä, 2006). Exogenously caused increments to monitoring supply should produce less time-constraints given that the additionally required advice can be split across a greater number of co-investors.

Hypothesis 2: Busy investments perform better if the VC firm holds primarily syndicated investments.

Whilst syndication mitigates the attention constraint for co-investors, much of the additional administrative management and interaction is delegated to the lead investor (Gorman and Sahlman, 1989; Wright and Lockett, 2003). Gorman and Sahlman (1989) find that lead investors interact 10 times as much with the syndicated investments.

Hypothesis 3: Busy investments of primarily syndicating VCs perform worse if those VCs are also primarily lead investors.

4. Methodology

4.1 Discussion on the Methodological Approach

An experiment to establish venture capitalists' ability to select companies that are poised to succeed, would be to eliminate the treatment effect of post-investment monitoring and compare company outcomes of screened yet rejected firms with non-VC-selected firms. It is, however, quite difficult to identify a setting that approximates this experiment since one, data on screened yet not selected firms does not, to the best of our knowledge, exist in any publicly available database. Second, given that monitoring represents VCs' primary activity, we cannot identify a setting where monitoring engagement is entirely eliminated. Comparing company outcomes ex-ante of VC and non-VC funded firms, on the other hand, (see e.g., Hellmann and Puri, 2002; Chemmanur, Krishnan, and Nandy, 2011; Puri and Zarutskie, 2012) would fail to consider the unobservable sorting that contributes to future outcomes. One a side note: if one were able to precisely identify the observable factors ex-ante that contribute to positive future outcomes, VCs would presumably have no competitive advantage in selecting firms more successfully. Another useful experiment would be to vary the level of involvement in the screening process but to leave the level of monitoring involvement unchanged. If differences in outcomes for portfolio companies are driven purely by post-investment monitoring, screening involvement should have no effect on company outcomes. While Abuzov (2020) uses VCs' active IPO process as an attention-grabbing event, the source of exogenous variation in VC screening involvement that we will exploit is the presence of industry shocks.

4.2 Variables

4.2.1 The Attention-Grabbing Event

Time is considered to be venture capitalists' scarcest resource. In the study by Kaplan and Strömberg (2001) for example, 20% of VCs were worried that they might spend too much time on post-investment monitoring activities. One potential reason are restrictive covenants in limited partnership agreements that limit VCs' ability to hire general partners with the required expertise when needed (Abuzov, 2020). Both monitoring and screening capacity are thus scarce with increased involvement in either having potentially adverse effects on the other. One way to think of the involvement of VCs is to frame it as a problem of VCs optimally allocating their attention across the portfolio of ventures. This framework appears plausible since we know that VCs economize on attention in substituting toward less-time consuming early-stage investment during adverse market conditions (see Yung, 2012) and select an optimal portfolio size to maximize the value of attention (see Jääskeläinen, Maula, and Seppä, 2006). If we consider a single VC partner who has a stake in two unrelated firms, he will divide his (fixed) time and attention in such a way so as to maximize the performance of his portfolio by increasing his involvement in any company to the extent that the marginal benefit of increased involvement equalizes across all firms in his portfolio (see Jääskeläinen, Maula, and Seppä, 2006). The monitor would thus increase his attention to a particular venture when the marginal benefit of higher involvement increases relative to the other ventures. In the same vein as Kempf, Manconi and Spalt (2017), we propose that this would be the case if part of the VC's portfolio were shocked by extreme positive and/or negative industry returns.

The Industry Shock

The general idea behind the industry shock is that more volatile shocks draw more attention because the value of attention increases with more uncertain outcomes (Kacperczyk, Nieuwerburgh, and Veldkamp, 2014). The economic fundamentals underlying the industry shock comprise unanticipated industry-specific changes in demand, technology, competitive landscape, and/or regulation (Kempf, Manconi and Spalt, 2017). VCs in turn sit on boards and are often actively engaged in day-to-day operations providing strategic and operational advice. Our hypothesis is that the introduction of unforeseen circumstances introduces novelty to the otherwise limited added value of VCs' fixed knowledge base. For example, suppose that a new technology enters the market with the potential of disrupting existing businesses' cost structure. The VC partner has previously acquired, through his/her other engagements, knowledge in that field and knows how to provide valuable advice, however, requires time to process, communicate and/or implement the information. Sudden adverse effects on venture performance may also trigger a recruitment process for more able management and since VCs are actively engaged in hiring; this process likely exacerbates distraction (Rajan, 2010; McMillan, Kulow and Khoylian, 1989). The potentially increased value of the VC activities raises the marginal benefit of increased involvement. The VC will subsequently raise his/her involvement to a level where the marginal benefit of involvement is yet again equated across the portfolio and, in consequence, reduce the involvement in the unaffected part of his/her portfolio.

To construct our industry-shock variable, we will turn to Wharton Research Data Services' (WRDS) industry return data. WRDS' industry classification is based on the popular (see Fodor, Jorgensen, and Stowe, 2021) Global Industry Classification Standard (GICS). GICS defines 10 different industries. WRDS draws its GICS industry monthly return data from the S&P industry indices. To generate the quarterly returns, we average across monthly returns for each quarter. Quarterly returns are available in an "equally-weighted" and "value-weighted" format. The latter considers the size of a given firm relative to the index, the former averages across firms, irrespective of size. In the context of the industry shock, the equally-weighted index provides the advantage of representing a greater diversity in extreme returns. If a given industry in the equally-weighted index exhibits extreme returns, it is more likely that a greater number of firms experiences this shock. The value-weighted index, on the other hand, might introduce bias from a few very dominant big players while a large fraction of firms are unaffected. To construct the industry shock variable, we therefore utilize the equally-weighted index given that the representation of industry shocks is broader increasing the likelihood that a given venture is affected.

A measure of distraction

While the industry shock introduces a broad measure of distraction, we argue that a shock to a given industry will not likely have the same attention-grabbing effect to every VC. Our main interest lies in constructing a firm-level proxy of distraction D, that increases when the VC shifts more attention from existing activities. Our conjecture is that a higher D will cause monitors to shift more attention towards the shocked portfolio and less to screening of non-shocked or "busy-investments". In Section 3.2 we argue that a shock to attention, i.e., a higher D, can equally affect monitoring involvement thereby introducing endogeneity to the model. However, because the industry shock lasts only for a quarter, we expect the imposed constraint to be negligible. On the other hand, it could be possible that the constraint reduces the probability of board membership altogether. Abuzov (2020) however, finds no relationship between the probability of board membership and a shock-induced busyness. We suppose that less time leads to less informed decisions (see Chen and Guay, 2020), inaccurate valuations and/or insufficient due diligence.

While a VC-partner or VC-fund distraction score might provide a more accurate representation of distraction, since firm-level distraction will consolidate distracted and non-distracted VC partner investments, VC partner-to-investment allocations would drastically increase the complexity of the data collection and reduce the sample size significantly since matches between BoardEx for the VC-partner level and VentureXpert for VC investments are only a fraction of either database's content depth. Instead, we will moderate D in order to capture a higher degree of firm-level distraction.

Our base-line measure of D follows the previously-developed intuition that a given VC partner of a VC firm will increase his/her monitoring involvement in the shocked portfolio while decreasing his screening involvement in firms unrelated to the shocked industry. Although it is theoretically possible that a VC partner only monitors and invests in the same industry at any point in time, we suppose that there is a frequent overlap and assume that the firm-level distraction D is a good proxy for the aggregate distraction of all VC partners. In line with the notion that VCs seek to maximize the performance of their portfolio and considering that increased attention is valuable (see Jääskeläinen, Maula, and Seppä, 2006), we moderate the impact of the distraction and expect the change in involvement to be proportionate to the invested capital of the shocked portfolio at quarter q divided by the total cumulative invested capital (i.e., current investment holdings) at q which we will denote as w_q^{IND}. Though invested capital might not represent the true importance of a particular venture to the VC (given changes in the exit potential), it is the only value we can measure. We define different measures of D, depending on a positive or negative shock, for each VC firm i, in calendar quarter q as:

$$D_{iq}^{IND-} = w_{iq}^{IND} \times IS_q^{IND-} \tag{1.1}$$

$$D_{iq}^{IND+} = w_{iq}^{IND} \times IS_q^{IND+} \tag{1.2}$$

Where:

$$IS_q^{IND-} = \begin{cases} 1, & Return = smallest\ in\ the\ set\ of\ IND \\ 0, & Otherwise \end{cases}$$

$$IS_q^{IND+} = \begin{cases} 1, & Return = largest\ in\ the\ set\ of\ IND \\ 0, & Otherwise \end{cases}$$

And:

$$w_{iq}^{IND} = \frac{Holdings\ of\ VC_i\ in\ IND}{Holdings\ of\ VC_i}$$

where IND denotes a given GICS industry.

Distraction intensity

We argue that D is higher in later-stage non-syndicated holdings or later-stage syndicated holdings of lead-investors. The degree of distraction should differ by the stage of investment since early-stage and seed stage investments typically have a longer exit horizon; immediate temporary shocks to an industry should therefore introduce less uncertainty and associated therewith, less of a need for increased monitoring involvement. One option to incorporate variation in distraction from the investment stage would be to define a score for seed/early-stage equal to 0 and later-stage equal to 1, average across the shocked portfolio of companies and multiply with w_q^{IND}. One problem with this approach is that we would make an implicit assumption about the relative contribution of each measure on distraction. For example, we would suppose that a portfolio with 100% late-stage investments contributes to investor distraction to the same extent as the industry shock itself. An alternative would be to classify VC firms at every q as either early-stage/seed stage investors, if the stage score-average is greater than the average across all VC firms in the sample during a given quarter, and as later-stage investors otherwise, devising different measures of D for every stage, i.e., interacting D with $stage$.

While the stage presumably moderates the importance of the industry shock, syndication allows the VC to reduce the time expended on individual ventures by distributing the additionally required advice across syndicate partners (see Jääskeläinen, Maula, and Seppä, 2006). In line with Abuzov (2020) we define syndicated investments as those with more than one VC investing in any given round and hypothesize that VC firms with a higher percentage of syndicated investments at a given q are less distracted by the industry shock. In the classification framework, we can extend every measure of $D \times stage$ by an indicator variable equal to 1 if the syndication score-average is greater than the average across all VC firms in the sample, otherwise equal to 0, so $D \times stage \times syndicate$.

Syndication enables co-investors to reduce their commitment and managerial resources while much of the management of the investment is delegated to the lead investor (Gorman and Sahlman, 1989; Wright and Lockett, 2003). Syndication thus mitigates the attention constraint for co-investors but exacerbates them for the lead investor. In the same vein, Gorman and Sahlman (1989) find that lead investors interact 10 times as much with the syndicated investments. The workload is furthermore increased by the administrative management of the syndicated investment (Wright and Lockett, 2003). Lead investors are commonly defined as those investors that have been with the company the longest (Gompers, 1996) and not those that have the largest equity stake. VCs originating the investment tend to be those that serve the most as an input to the venture's development and have the highest probability of board membership (Gorman and Sahlman, 1989). We therefore hypothesize that primarily-syndicating VC firms that primarily act as lead-investors (again with the arbitrarily chosen average as the cutoff point) will be more distracted, all else being equal. We adjust Gompers' (1996) measurement of *leadinvestor* since syndicates may be present at the initial investment level: we define *leadinvestor* as the investor who has been with the venture the longest and has the greatest stake at the initial round. If the portfolio company outcomes are attributable to the distraction event, we therefore expect the distraction effect to be stronger for *D* × *laterstage* × *nonsyndicated* × *leadinvestor* and *D* × *laterstage* × *syndicated* × *leadinvestor* having no particular differential expectation about positive or negative shocks.

Timing of the Distraction

One problem with the timing of the screening process is that it is unobservable in the data. However, we know that the average deal takes 83 days to close (Gompers et al., 2020) and that investment dates are reported. Since we measure investment dates and industry shocks at the quarter-level, we cannot, however, ascertain that the effect is only evident in the investment's quarter: for one, if the investment were at the beginning of the quarter, we could well expect the effect of busyness to be present in quarter q-1. Conversely, if the investment were made at the end of a quarter, with VCs either anticipating an imminent industry shock or the effect of the shock coinciding with the previous quarter, we could expect a forward-looking measure of (D_{iq}^{IND}) to induce busyness. In fact, our data exhibits a strong bias towards the end of the quarter with most investments undertaken in month 6,9, and 12. To test the relationship between distraction and portfolio company outcomes dynamically, we include lagged and forward-looking measures of (D_{iq}^{IND}). (D_{iq-1}^{IND-}) for example, is the equally-weighted negative industry shock induced-distraction in the quarter prior to the investment. We hypothesize that (D_{iq-1}^{IND}), (D_{iq}^{IND}) and (D_{iq+1}^{IND}) have an effect on investments.

4.2.2 Dependent Variables

The main dependent variable is $\log(MOIC + 1)$ which provides a measure of the effect of compromised screening on the performance of a given investment. *MOIC* is computed as the fraction of total funds invested and the exit value. Total funds invested are the cumulative *estimated equity amount*, a variable by Refinitiv Eikon, raised by a given portfolio company. The exit value will be equal to the transaction value if acquired, equal to the IPO exit value if the company goes public, and 0 otherwise. As a secondary dependent variable, we seek to determine the change in the probability that a firm gets acquired or goes public if the investment was selected by a busy VC firm. We set the indicator variable *exit dummy* equal to 1 if a firm gets acquired or goes public, and 0 otherwise.

4.2.3 Omitted Variables

Busyness is the framework of the venture capitalist's portfolio of ventures is not invariably value-destructive as discussed in Section 2.3. In particular, Jääskeläinen, Maula, and Seppä (2006) argue that there is an optimal portfolio size with a trade-off between "over-monitoring" as well as the diminishing return on the fixed knowledge base and the marginal benefit of involvement. *Busyness* in Jääskeläinen, Maula, and Seppä's (2006) framework is defined as the average number of VC partners divided by the average number of ventures in the portfolio. If this measure of busyness were correlated with D, inference would break down. However, while *busyness* is an intrinsic proxy of VCs' attention capacity, D is merely a constraint of and exogenous to the intrinsic attention capacity of VCs. A potential serial correlation should be accounted for by *year* fixed effects. The treatment intensity measures *stage*, *syndicate* and *leadinvestor* may, however, be negatively correlated with *busyness:* a focus on more time-intensive forms of investment may induce VC firms to increase their workforce in the long-term and decrease *busyness* as a result. Depending on whether a VC firm is below or above its optimal portfolio, *busyness* might either be positively or negatively correlated with portfolio company outcomes. The direction of bias is therefore unclear. Because of the sample collection issues discussed in Section 4.2.1, *busyness* is omitted in our analysis but might have an effect on our results.

4.3. Empirical Methodology

Industry shocks cause VCs to re-allocate their attention temporarily so that new investments in unaffected industries are screened with less due diligence. If VC involvement in screening matters, then temporarily loser attention should translate into lower multiples and a lower probability of an IPO or M&A. To estimate the effect of temporary industry shocks on portfolio company outcomes, we employ the following baseline specification:

$$Y_{is} = \beta_0 + \beta_1 D_{isq}^{IND+} + \beta_2 D_{isq}^{IND-} + \beta_3 \boldsymbol{X}_{sq} + \varphi_i + \gamma_l + \theta_q + \varepsilon_{isq} \tag{2}$$

Where:

$$D_{isq}^{IND+} = \begin{cases} D_{iq}^{IND+}, & IND^{+} \neq IND_{s} \\ 0, & Otherwise \end{cases}$$

$$D_{isq}^{IND-} = \begin{cases} D_{iq}^{IND-}, & IND^{-} \neq IND_{s} \\ 0, & Otherwise \end{cases}$$

and i denotes the VC firm, s the portfolio company, q the quarter of the investment, and l is the industry of the portfolio company. D_{isq} is the vector of interaction terms capturing different measures of distraction intensity, equal to 0 if the industry of the venture is the same as the shocked industry so as to avoid the effect of changes in market conditions on portfolio company outcomes. β_1 and β_2 are the coefficients of interest and are hypothesized to be negative. Y denotes the portfolio outcome variables comprising the *MOIC* and an indicator variable capturing whether a portfolio company goes public or is acquired. $\boldsymbol{X}_{sq}$ is a vector of time-variant investment-level controls adopted from Abuzov (2020) including the syndicate size, the round number, the funds invested in a given round, and the total funds raised for a portfolio company (see Table T.19 for variable definitions). θ_q denote year and quarter fixed effects and account for the potential influence of time-variant endogenous effects, i.e., general time-dependent trends in the VC market. γ_l are portfolio industry fixed effects. All specifications use robust standard errors clustered by the VC firm. Although IS_q^{IND} is only equal to 1 if $IND \neq IND_s$, we could still expect a shock in a given industry to be influenced by positive or adverse market conditions since IS_q^{IND} is defined as a relative measure. Yung (2009) in turn argues that improving market conditions decrease the average intrinsic quality of ventures while increasing in deteriorating conditions. In this light, we would like to exclude the possibility that IS_q^{IND} is driven by external market conditions that drive an equivalent change in IND_s since improving or deteriorating conditions drive the intrinsic quality of ventures on the market with the potential of influencing our dependent variable. Robustness tests will control for these industry shocks through the inclusion of *time* × *industry* fixed effects. Lastly, to test whether the distraction effect holds in later rounds, additional robustness tests will further interact D_{isq} with the round number.

The use of panel data is a crucial aspect of our methodology for several reasons. First, Abuzov (2020) finds that VCs with prior IPO experience know how to navigate the IPO process more efficiently and are thereby not as distracted as non-experienced VCs. This ties in with

Bennedzen, Péréz-Gonzáles and Wolfenzon (2010) who argue that the effect of a distraction event is a function of economic agents' (in their case CEOs) intrinsic ability to withstand a distraction event and the actual change in involvement. In a pooled OLS specification, if ability to withstand shocks were not constant across VCs, then predicted performance would capture both the variation of the VCs' ability to withstand shocks and the actual impact of the distraction event on the level of involvement. Greater ability in withstanding the shock would cause the distraction event to have lower influence on the outcome variable and thereby introduce endogeneity in the model. Although strictly speaking ability is a characteristic of economic agents, we suppose that a VC firm is simply a collection of abilities that are near time-independent.

Second, there are several omitted VC firm-dependent characteristics that could potentially exacerbate or mitigate the effect of D on portfolio company outcomes. Independent VC firms have a higher likelihood of serving on boards, (see Section 2.2.2) and, given that the industry shock causes increased involvement in monitoring, independent VC firms would be less exposed to D. Unfortunately, however, we have no measurable variable of what constitutes an independent VC firm. Furthermore, if we suppose that Jääskeläinen, Maula, and Seppä's (2006) *busyness* is approximately time-independent, then higher levels of *busyness* would correlate with D cross-sectionally given a higher time constraint on VC partners. Additionally, given that the degree to which venture capital firms use a formal process during pre-investment screening is related to the size of the firm (see Section 2.2.1), we could expect D to be smaller for larger-sized firms that can more easily re-deploy resources. Lastly, high-reputation VC firms attract better investments and therefore devote less time to find good investments. The effect of D would be less pronounced for these firms. To exclude the unobserved heterogeneity, we adopt Abuzov's (2020) methodological approach and include *VC firm* fixed effects denoted φ_i. Notwithstanding the potential correlation of the VC-dependent error term and D, Roberts and Whited (2013) argue that both fixed effects and random effects specifications should be estimated and tested using the Hausman test given that fixed effects can exacerbate measurement problems (Griliches and Mairesse, 1995) and reduce efficiency (Roberts and Whited, 2013).

4.4 Data

Data on VC investments and exits in this paper has been collected from Refinitiv Eikon's (formerly Thomson Reuters Eikon) private equity screener. The S&P GICS industry return data was collected from Wharton Research Data Services (WRDS). We deem both databases as reliable, and they are globally available which should help make the paper, in the context of data, both reliable and replicable. The data was retrieved through three different spheres of the two databases. VC investments were collected through the 'deal' universe of Refinitiv Eikon's private equity screener and the exits were retrieved from the 'exit' universe on the same database.

The 'deal' universe offers the equity amount invested into a given venture at a given investment date by a given VC firm as well as the current portfolio status ('currently', 'formerly', 'unknown') and company status (e.g., 'acquisition', 'IPO', 'bankruptcy', 'active' etc.). The 'deal' universe would therefore allow us to run the outcome equation (3) on former investments with an indicator variable 1 if the status were equal to 'acquisition' or 'IPO' and 0 otherwise. However, only the 'exit' universe offers the exit date and transaction amount. The former is necessary to construct VC portfolio holdings for a given quarter so that w_q^{IND} can be estimated. The latter is required to calculate the *MOIC*. That is, even when the deal universe provides the indication that an investment is no longer backed by a given VC firm, we can use a former investment in equation (3) only if we can match the investment with an exit. Investments and exits are not connected within Refinitiv. Ventures can have multiple investment rounds at different stages with multiple exits. We match investments with exits by minimizing the days passed between investment date and exit date with the condition that the difference is greater than 0. Active investments are considered part of VCs' holdings and will contribute to w_q^{IND} and are hence added to our data. We start with a sample of 108 thousand former investments between 1996 – 2021 and consolidate investments of the same VC within the same round. We are left with 97 thousand former investments and of those can match 59 thousand investments. This means that 38 thousand investments are unaccounted for that would otherwise contribute to D. To define portfolio holdings at any quarter, we further add 41 thousand current investments, and we define the "exit date" as the current date. The industry returns were collected from WRDS and their database Compustat. The three datasets were then matched together in order to create a combined dataset containing the necessary variables.

4.4.1 Missing Data

During the data collection process, we encountered missing values at two different levels. On one hand, former investments that, by definition, should have an exit date with no assignable exit date, and on the other hand, known M&A/ IPO exits with transaction values of 0. The former is required to construct w_q^{IND}. The latter is necessary to evaluate the *MOIC*. There were a total of 38 thousand investments with no assignable exit date after the matching process. There are a couple different approaches in dealing with such a problem (Hair, Page and Brunsveld, 2020, p. 328). The first approach discussed is to eliminate those observations that have missing values. In order to do this without making the final model biased is to understand whether the missing values are systematic or random. If the missing data is systematic, it will create a problem for the model and make it biased. This is because if the missing data is systematic, the rest of the observations will not represent the population in a reliable way. If the missing data is random, then it can be argued that the remaining observations still represent the population, and the model will remain reliable. Another possible way of dealing with the missing data is through a process called imputation. This is done by replacing the missing values with a measure based on the data which have the values available, usually with the mean or median. This method is only viable if the data is metrically measured variables (Hair, Page and Brunsveld, 2020, p. 328) which is not the case for exit dates. Therefore, will we go through with the first option and eliminate the observations. There are statistically significant differences in the mean between the data missing the exit date and the data with it available for some of the variables. This was calculated using t-tests in Stata (see Appendix 1). The investments for the companies not having data on the exit date are generally done in earlier rounds, they have lower equity invested in the company and lower fund equity invested which is reasonable given the lower equity invested. This could be worrisome since it could be an indication that the data missing is systematic. This is, however, difficult to assess and the difference in mean between observations for the two groups is not conclusive in whether the missing data is systematic or random. By still having a large number of observations after the elimination of the observations missing the exit date, we will hopefully still have a reliable and unbiased model. Further, the size should be beneficial as a large sample size generally increases the precision of the sample (Bryman & Bell, 2015, p. 198). Moreover, it should be noted that this removal could potentially create some bias in the model and may weaken the model. The removal was a necessity nevertheless in order to create the empirical model as the exit dates are vital for the model to work.

Another potential issue was that a substantial number of observations regarding M&A related exit values had the value of 0. In order to make sure that this was not missing data we observed that when collecting data from Refinitiv Eikon and missing values are present, it will not be shown as 0 but instead as a blank cell. We therefore concluded that these values were accurate.

4.5 Descriptive Statistics

Our final sample includes 45 772 investment observations based on US VC firms and US portfolio firms. The sample contains investments from 1999 to 2021 and Table T.1 shows the descriptive statistics for the relevant variables used in our regressions. The panel contains investments from 87 quarters from Q3 1999 to Q1 2021. In the sample there is 28.35% investments which are counted as distracted, however, as previously discussed the distractions have a score determining how much impact that distraction has on a VC firm's involvement. Moreover, in Table T.1 we can also observe that a negative distraction i.e., a distraction when the industry is having low returns, has a larger distraction score on average in comparison to the positive distraction. We can also observe that the exit multiple (*MOIC*) has an average of 1.75 but the median is 0 which is an indication that there may be some large outliers that are increasing the mean. An example of this is the maximum value of *MOIC* which is 3986.6 and is far greater than the mean and the median. We will therefore winsorize at the 99th percentile in the right tail in order to handle such outliers. The number of observations at any given year can be seen in Figure F.1 and has a few notable changes. Firstly, there is a large increase in investment observations in 2000 compared to 1999 which is due to the fact that our sample only captures the last two quarters of 1999 and not the entire year. There is also a major drop in investments in 2001 which is important to note. The drop is likely a consequence of the ''dotcom bubble'' bursting in 2000. Further, the largest industry sector in the sample is information technology (as shown in Table T.3) which further gives substance to the claim that the dotcom bubble is the reason behind the drop. Furthermore, another drop is present between 2008 and 2009 which similarly to the drop in 2000 is likely due to the financial crisis of 2008. Lastly, we can observe that there is a constant decline the last 10 years in investment observations. This is because we measure performance based on exits and the later an investment is made, the less likely is a portfolio company of having exited their VC-backing yet. As we exclude portfolio investments when there is no exit yet, the sample decreases the closer to the present day an investment is made. The volatility in the observations per year is therefore reasonable and there are not any indications that the sample is biased in this regard.

Table T.2 show descriptive data for distracted and non-distracted investments separately as well as the difference between the two clusters. As previously mentioned, are 28.35% of the investments made when a VC firm is distracted. It is generally more common for distracted VC firms to be the lead investor compared to non-distracted. Furthermore, distracted VC firms also tend to invest in earlier stages in comparison to non-distracted firms, but it is a marginal difference. A similar difference is present in the syndication dummy where distracted VC firms tend to be marginally less syndicated for those investments. The VC firm is also more often the lead investor in distracted investments. The distracted investments have a lower mean in regard to their exit i.e., they are generally less likely to exit through either an IPO or an M&A compared to non-distracted investments. This is expected since the notion previously discussed (see Section 4.2.1) that distracted investments should lead to a lower amount of exits through IPOs and M&As (Abuzov, 2020). The *MOIC* is also lower for the distracted investments which is expected based on similar arguments as for the IPO/M&A *exit dummy*. There are not any major differences in relation to which round an investment is made, the mean of investment round is marginally lower for distracted investments, but the median is the same for both clusters. The differences between the two clusters are quite expected and the dependent variables *MOIC* and the M&A/IPO *exit dummy* are expectedly lower for the distracted investments.

Table T.3 contains the descriptive data clustered by each of the 10 GICS industry sectors. The two largest industries are as mentioned information technology and the second largest is health care. Together they represent about 80% of all observations, 51% and 29% respectively. This is expected as software companies attract the most venture capital with biotechnology being in second place (Hallet, 2017). Software is captured in information technology and biotechnology is within health care. Therefore, is the dispersion of the observations between the industries not unrealistic and the sample may represent the population in this aspect. Furthermore, there are 5 sectors with lower than a 1000 observation including financials, consumer staples, materials, energy, and utilities. Because of the small size of these clusters, we can observe some anomalies with the *MOIC* for the financial sector as an example. The mean for the *MOIC* in the financial sector is 8.57 which is much larger compared to the mean of the total sample which is 1.75. Because the observations are quite low in this sector, the outliers will have a greater effect on skewing the mean which is likely the case in this situation. Further, when winsorized, this problem should be mitigated. We can also observe that for the five industries where the number of observations is below 1000 there is generally a lower exit dummy. Within the sectors with more than 1000 observations, we can observe that communication services has the highest average *MOIC*, and health care has the highest median. The health care also has the highest average *exit dummy*, but the averages in this category are quite similar with consumer discretionary being an exception. Interestingly is health care also the sector with the lowest average positive distraction score and the second lowest average negative distraction score. This is reasonable since the sector as mentioned have the highest median for *MOIC* and the highest average *exit dummy*.

Table T.4 contains the frequency of distractions for each year as well as the weight of the frequency in relation to the total number of observations for either distracted or non-distracted investments. The percentage of distracted investments are notably larger in a couple of years compared to the total percentage of investments that year. One such example is 2000 where the distracted investments make out 13.74% of all the distracted investments while all the investments make out just 9.72%. This is likely due to the dotcom bubble bursting as previously mentioned which created difficulties for companies, especially in the information technology sector. Interestingly, there is not a similar effect in 2008 when the financial crisis occurred. When observing the change in investment observations per year (see Figure F.1) we could see a drop in observations between 2008 and 2009 similar to the one between 2000 and 2001 but the financial crisis does not seem to have created the same distractedness as the dotcom bubble did in 2000. This could be because the 2000 crisis affected the companies in our sample more directly with information technology being the largest sector (see Table T.3) while the financial crisis of 2008 had a more general effect on how much capital could be invested from VC firms. Figure F.2 depicts the total number of observations per year as well as the fraction of distracted investments each year.

4.5.1 VC Fund-Level

On the VC fund-level our sample contains 31,514 investment observations from Q3 1999 to Q1 2021. Furthermore, 13.18% of the observations in the sample are distracted investments (see Table T.5) which is lower than the percentage of distracted investments in the firm-level sample (28.35%). Consequently, we observe a lower average distraction score for the fund-level sample both for positive and negative shocks. Similar to the firm-level sample is the distraction score higher for negative shocks compared to positive shocks. The average *MOIC* is also similarly to the firm-level sample higher in comparison to the median which is also likely due to large outliers. When observing the number of observations per year for the VC fund-level sample in Figure F.3 we can observe very similar trends to the firm-level sample (see Figure F.1) which is likely due to the same causes as discussed in section 4.6. Therefore, can possibly the fund-level sample also disregard bias in this regard.

In Table T.6 we can observe the differences between distracted and non-distracted investments. Distracted investments tend to be the lead investor more often, they marginally more often invest in earlier stages as well as they are less often syndicated investments. This is in line with the data for the firm-level sample (see Table T.2). The *MOIC* and the *exit dummy* is also expectedly lower for the distracted investments compared to non-distracted investments. The difference in average round number is marginal with non-distracted investments being made in later rounds which is also similar to the firm-level sample. The fund-level sample and firm-level sample are similar in the differences between the distracted cluster and the non-distracted cluster. One exception is that syndication seem to be less prevalent in the fund-level sample with a mean of about 0.6 and 0.5 for non-distracted and distracted investments respectively. This is lower compared to the firm-level where the mean for non-distracted investments is about 0.64 and for distracted investments 0.62.

In Table T.7 we can observe the descriptive statistics clustered by industry for the fund-level sample. The two largest industry sectors in this sample are just like the firm-level sample information technology and health care. Information technology represents 48.95% of the total number of observations and health care represents 31.60%. As discussed in section 4.6 is this a reasonable dispersion since software and biotech companies are the two types of firms which attracts the most venture capital (Hallet, 2017). Furthermore, we can observe that 5 industries have above 1000 observations and five below 1000. Further, it is the same five industry sectors as the five for the firm-level sample. For the sectors with above 1000 observations, we can see that industrials have the highest average *MOIC,* and health care have the highest average *exit dummy*. Health care having the highest average exit dummy is consistent through both the fund-level and firm-level samples. For the industry sectors with fewer number of observations there are some anomalies such as the large average *MOIC* of 10.23 within consumer staples. This is likely due to the sample size being small and therefore could it be more exposed to outliers. The dispersion between the industry sectors is similar to the dispersion in the firm-level sample which is expected as some industries receive more VC backing compared to others (Hallet, 2017).

Table T.8 contains the frequency of distracted investments on a yearly basis and the weight of the frequency in regard to the total number of observations. Similar to the firm-level sample (see Table T.4) there is a large fraction of distracted investments (14.68%) compared to the total fraction of investments (10.13%) in 2000. As argued in section 4.6 this may be because of the dotcom bubble which occurred in 2000. A similar effect cannot be found in 2008 similarly as in the firm-level sample. This even if there was a drop in observations between 2008-2009 similar to the one between 2000-2001 (see Figure F.3). The lack of distracted investments in 2020 and 2021 is likely due to the small number of observations in those years as well as the lower number of distracted investments in the fund-level sample.

5. Empirical Results

5.1 Baseline Results

In the baseline regression model (see Table 1) we report the effect of (D_{iq}^{IND}), absent of interactions with *syndicate*, *leadinvestor*, and *stage*, on the likelihood that a venture goes public or is acquired and *MOIC*. We control for VC firm and investment round characteristics, the total amount invested into the venture as well as time and industry fixed effects. Columns 4-6 of Table 1 report that the likelihood of exiting via acquisition or IPO is 3.8% lower for ventures of overperforming industry shocked VCs, and 5.1% lower for underperforming industry shocked VCs. The results are statistically significant at the 1% level for (D_{iq}^{IND-}) and at the 5% level for (D_{iq}^{IND+}). When we introduce clustered robust standard errors our certainty of inference decreases to 5% for (D_{iq}^{IND-}). The probabilities can be interpreted as the decreased likelihood that would be incurred if the entire portfolio were shocked. With a mean value of just 0.02 for (D_{iq}^{IND-}) and 0.018 for (D_{iq}^{IND+}) the reported probabilities accordingly do not

Table 1: Baseline Regression Results

Main regression results for D_{iq}^{IND-} and D_{iq}^{IND+} regressed on MOIC and the indicator variable equal to 1 if a venture was acquired or went public. Controls comprise the amount raised in a given round, the round number, the size of the syndicate, and the total funds raised by a given venture prior to the assigned exit date. Regression was conducted using fixed effects estimation, with standard errors clustered by the VC. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1 denote the statistical significance.

	log(MOIC+1)			*Exit Dummy*		
	(1)	(2)	(3)	(4)	(5)	(6)
	FE	FE	FE, clustered robust	FE	FE	FE, clustered robust
D_{iq}^{IND-}	0.027	0.017	0.017	-0.051***	-0.051***	-0.051**
	(0.035)	(0.035)	(0.034)	(0.018)	(0.018)	(0.021)
D_{iq}^{IND+}	0.060*	0.049	0.049	-0.039**	-0.038**	-0.038**
	(0.035)	(0.034)	(0.040)	(0.018)	(0.018)	(0.018)
Controls	No	Yes	Yes	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
VC Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.090	0.306***	0.306***	0.928***	0.928***	0.928***
	(0.082)	(0.082)	(0.077)	(0.043)	(0.044)	(0.060)
Observations	45,297	45,297	45,297	45,753	45,753	45,753
R-squared	0.008	0.036	0.036	0.020	0.021	0.021
Number of VCID	3,413	3,413	3,413	3,434	3,434	3,434

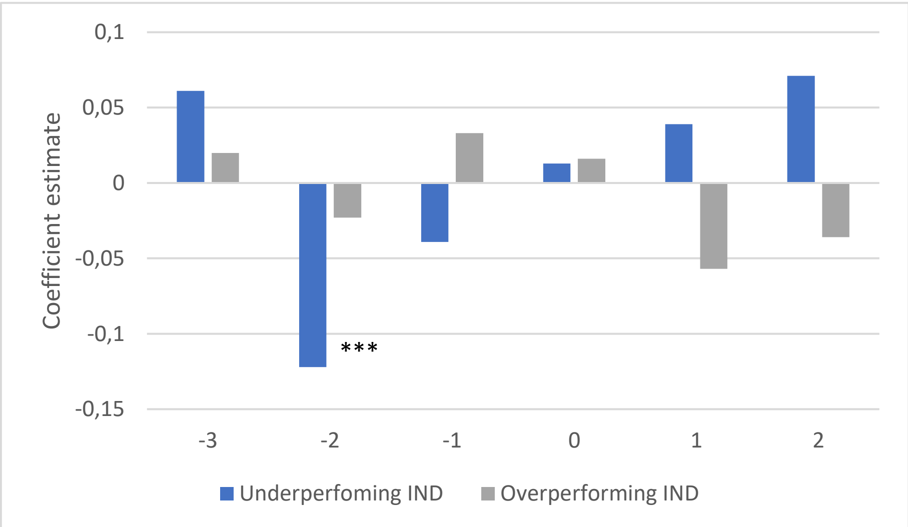
represent the reality of incurred busyness in the sample. Regressing *log(MOIC+1)* instead on the logs of *D*, we find that the likelihood of a venture's exit via IPO or M&A decreases by 0.046% - 0.06% for every percent increase in busyness, suggesting minimal economic magnitude of the busyness coefficients (see Table T.9). Table T.9 columns 1-3 furthermore suggest that busyness measured in the investment quarter is not sufficiently prevalent to cause a drop in *MOIC*.

5.1.1 Dynamic Effects

Figure 2 (Table T.10 for regression results) reports that *MOIC*, while not affected by an industry shock in the investment's quarter, is in fact adversely influenced by underperforming industry shocks incurred in *q-2*. A one percent increase in busyness is predicted to decrease *MOIC* by 0.122%. The coefficient is statistically significant at the 1% level with inference remaining unchanged using robust clustered standard errors. The lagged effect of (D_{iq-2}^{IND-}) suggests that either underperforming industry-shocks take more time to reach ventures or that VCs delay their response. In the survey by Gorman and Sahlman (1989), troubled investments are reported by VCs to be primarily the result of ineffective senior and functional management. Other contributing factors comprise ventures failing to capture market share, market and/or product problems. In this light, underperforming industries may exacerbate or induce market

Figure 2: Dynamic Effects - MOIC

Regression results for lagged and forward-looking measures of $ln\ (D_{iq}^{IND}+1)$ with the blue series reporting the coefficient of $ln\ (D_{iq}^{IND-}+1)$ regressed on log(MOIC+1) and the grey series the coefficient of $ln\ (D_{iq}^{IND+}+1)$ regressed on log(MOIC+1). The x-axis represents the lag relative to the quarter of the investment. Standard errors are robust and clustered by VC. The y-axis represents the coefficient estimates. Controls and fixed effects are included.

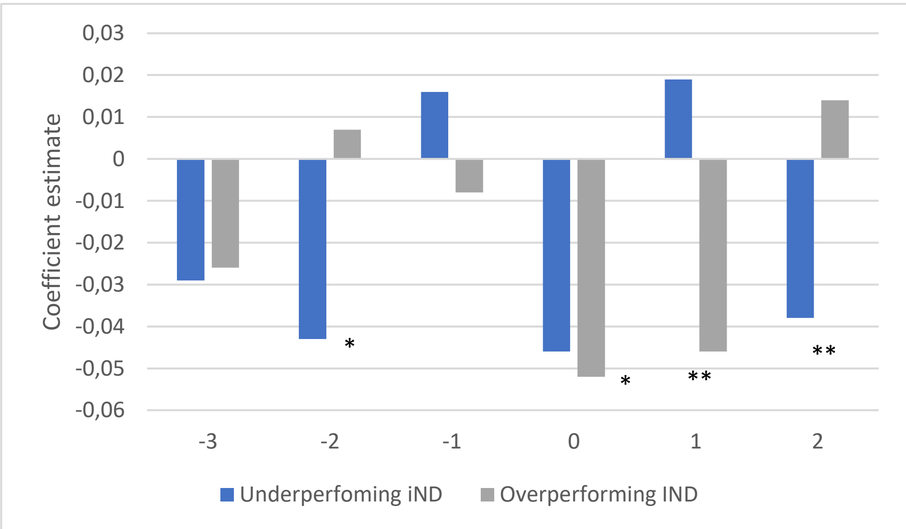


and/or product problems. If senior management fails to provide an effective solution during the underperforming quarter, we could expect VCs to hire new senior management after the fact. The response would in that case be delayed.

Figure 2 reports that inference for the coefficient of (D_{iq}^{IND-}) is reduced to a 10% statistical significance which means that some of the variation in the *exit dummy* variable was driven by lagged and forward-looking measures of (D_{iq}^{IND}). In particular, the coefficient of (D_{iq}^{IND+}) is increased in its economic magnitude from initially -0.038 to -0.052 in *q* and -0.046 in *q+1*. The results suggest that busyness primarily reduces the likelihood of exit via IPO or acquisition when the industry shock is imminent or occurs in the same quarter as the investment. The results furthermore confirm our initial hypothesis that a bias toward later-quarter investments and the potential for anticipation of imminent shocks cause forward-looking measures of *D* to affect portfolio company outcomes. However, along with the delayed response of VCs to underperforming industry shocks, we would expect this effect to be uniform irrespective of the dependent variable employed since both measures fundamentally capture the same concept of financial success. Abuzov (2020) similarly reports statistical and economic significance in the same time span irrespective of whether the *MOIC* or the *exit dummy* is employed as a dependent variable.

Figure 2: Dynamic Effects - Exit Dummy

Regression results for lagged and forward-looking measures of $ln\ (D_{iq}^{IND}+1)$ with the blue series reporting the coefficient of $log\ (D_{iq}^{IND-}+1)$ regressed on the Exit Dummy variable and the grey series the coefficient of $log(D_{iq}^{IND+}+1)$ regressed on Exit Dummy variable. The x-axis represents the lag relative to the quarter of the investment. Standard errors are robust and clustered by VC. The y-axis represent the coefficients. Controls and fixed effects are included.



The lack of economic magnitude of the estimated busyness coefficients and uniformity in the effect of busyness on the dependent variables raises questions about the validity of our measure of distraction at the VC firm level, i.e., the degree to which *D* actually measures distraction. Problems of validity can arise from at least two, not mutually exclusive, grounds: one, we assume that there are sufficiently many VC partners that have an interest in shocked ventures that simultaneously screen ventures in the non-shocked industries. This is presumably, what we capture with the w_{iq}^{IND} term. Although VC partners might manage several funds (Abuzov, 2020), funds and VCs partners may specialize in certain industries (Metrick and Yasuda, 2010), thereby limiting the effect of distraction. Two, the existence of restrictive covenants in limited partnership agreements (LPA) limit VC partners' ability to work for funds at the same time (Gompers and Lerner, 1996). Both factors contribute to a higher likelihood of non-distracted VC partners being consolidated with distracted VC partners with any potentially measurable effect being washed-out. At the fund-level, w_{iq}^{IND} should be more accurate since VC partners typically collaborate closely (Gompers and Lerner, 1996). We subsequently repeat our estimations at the fund-level to achieve a more granular measure of busyness.

5.2 VC Fund-Level

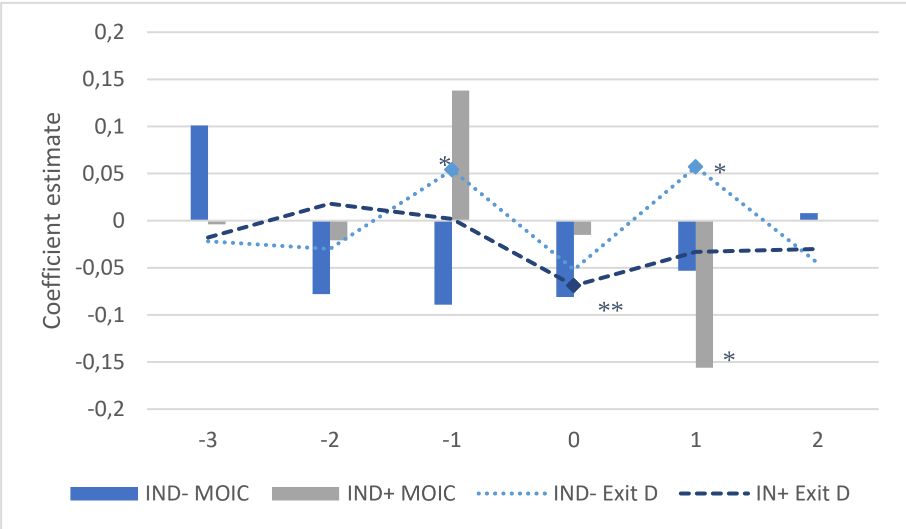
The coefficients of busyness regressed on the *exit dummy* at the VC fund-level show the same sign and economic magnitude as those estimated at the VC firm-level (see Table T.11). The estimates, however, are not statistically significant. Busyness regressed on *MOIC* similarly produces economically and statistically insignificant parameter estimates. Because the timing of screening is unobservable, we repeat the regression for dynamic effects.

5.2.1 Dynamic Effects at the Fund-Level

The lagged effect of (D_{iq-2}^{IND-}) regressed on *MOIC* at the VC firm-level could not be replicated at the VC fund-level (see Table T.12). The (D_{iq-2}^{IND-}) coefficient is considerably reduced in its economic magnitude and not statistically significant. These results suggest that the effect of (D_{iq-2}^{IND-}) on *MOIC* at the VC firm-level was in fact driven by factors other than busyness given that the VC fund level measure of *D* should produce a more accurate representation of busyness. Figure 3 reports an economically minimal but statistically significant adverse effect of (D_{iq}^{IND+}) on the likelihood of exit via M&A or IPO. Overall, the results, however, provide insufficient evidence to infer an economically meaningful effect of the sole measure of *D*, absent of interactions with *syndicate*, *leadinvestor*, and *stage*, on the financial success of VC portfolio companies. To determine whether the effect of D changes in any meaningful way when we introduce known measures of distraction, in the next section we will interact D with *syndicate* and *leadinvestor*. To strengthen the effect of the industry shock on distraction, we will further differentiate VC funds according to whether they primarily invest in early-stage or later-stage ventures and interact $D \times syndicate \times leadinvestor$ with *stage*.

Figure 3: Dynamic Effects at the Fund-Level – MOIC and Exit Dummy

Regression results for lagged and forward-looking measures of $log\ (D_{iq}^{IND} + 1)$ regressed on *log(MOIC+1)* represented by bars, and $log(D_{iq}^{IND} + 1)$ regressed on the exit dummy represented by the dotted lines. The x-axis represents the lag relative to the quarter of the investment. Standard errors are robust and clustered by VC fund. The y-axis represents the coefficient estimates. Controls and fixed effects are included.



5.2.2 Treatment Intensity at the Fund-Level

If adverse effects of temporary increments in the monitoring supply caused by industry shocks are indeed attributable to the effect of busyness, we expect the effect to be greater (smaller) for VCs that are more (less) time-constrained. Similar to Abuzov (2020) who interacts the occurrence of IPOs with the size of the IPO as a measure of busyness, we interact $log(D_{iq}^{IND} + 1)$ with *syndicate* and *leadinvestor*. The results of $log(D_{iq}^{IND} + 1)$ regressed on *log(MOIC+1)* are somewhat in line with our initial hypothesis (see Table T.13). We achieve meaningful economical magnitude of the busyness coefficient for syndicating, “lead-investing” VC funds where a one percent increase in busyness is predicted to decrease *MOIC* by -0.227%. The coefficient is statistically significant at the 10% level. Although we would theoretically expect the adverse effect of busyness to be greatest for non-syndicating, lead-investing VC funds, since that match is, at the investment level, practically not possible the most accurate measure of what constitutes lead-investing funds, presumably is represented by *syndicate* = 1, *leadinvestor* = 1. We see the same economically meaningful adverse effect of busyness with the *exit dummy* as the dependent variable: a one percent increase in busyness incurred by primarily syndicating, lead-investing VC funds is predicted to decrease the likelihood of exit via IPO or acquisition by 0.229%. The coefficient is statistically significant at the 5% level. Table T.13 column 2 furthermore reports a positive economically and statistically significant effect of non-syndicating, non-lead-investing VC funds and an economically and statistically significant negative effect of syndicating, non-leading-investing VC funds. In our framework, this would suggest that syndication, in contrast to our hypothesis, increases busyness on the VC fund level, and "single investment" leads to decreased busyness. Although the same effect does not substantiate with *MOIC*, we must seriously question the validity of the results given both a strong theoretical and empirical foundation for the effect of syndication on busyness (see Jääskeläinen, Maula, and Seppä, 2006). An alternative explanation for the effect may be found in the decision of VCs to syndicate in the first place. The primary motive for syndication arises from portfolio theory whereby capital investment is best shared when the deal is especially risky. Syndication thereby allows VCs to suppress idiosyncratic risk (Yung, 2012). In this light, we could argue that exogenous industry shocks influence idiosyncratic risk of unaffected ventures since IS_q^{IND} is defined as a relative measure (see Section 4.3). Syndication then acts as a mechanism to suppress increased idiosyncratic risk from industry shocks and is therefore correlated with IS_q^{IND} while idiosyncratic risk presumably decreases the likelihood of exit via acquisition and M&A. To exclude any potential effect of syndication, we will allow *syndicate*, as a stand-alone term, to correlate with the dependent variables and furthermore include *quarter* × *industry* fixed effects to exclude the possibility that our results are driven by time-variant industry shocks.

The results in Table T.14 confirm that some of the variation in the *exit dummy* was driven both by time-variant industry shocks and direct effects of *syndicate.* The positive busyness coefficient lost much of its economical magnitude and decreased to a 10% statistical significance. The negative busyness coefficient of syndicating, non-lead-investing VC funds, however, retained its statistical and economical significance suggesting that *syndicate* is not a primary driver in mitigating busyness in our sample, and that there are likely unobservable factors that drive busyness that are correlated with *syndicate*. Our hypothesis of the effect of busyness on portfolio company outcomes, however, is in so much confirmed that we see a significant adverse effect of busyness of VC funds that are syndicating and lead-investing: a one percent increase in busyness is predicted to decrease the likelihood of exit via IPO or M&A by 0.234% which is substantially stronger than the sole effect of *D* on the *exit dummy* and other measures of treatment intensity. These results are in line with the considerable time expended by VCs as lead-investors.

The interaction of the *syndicate* × *leadinvestor* combinations with *stage* regressed on the dependent variables produce coefficients that are not in line with the hypothesis that later-stage-investing VC funds are more strongly affected by busyness induced industry shocks (see Table T.15). *Stage* therefore does not serve as a valid measure of increased VC distraction and will consequently be disregarded in any further analysis. As with our previous analysis, we will repeat the regression of treatment intensity under consideration of dynamic effects.

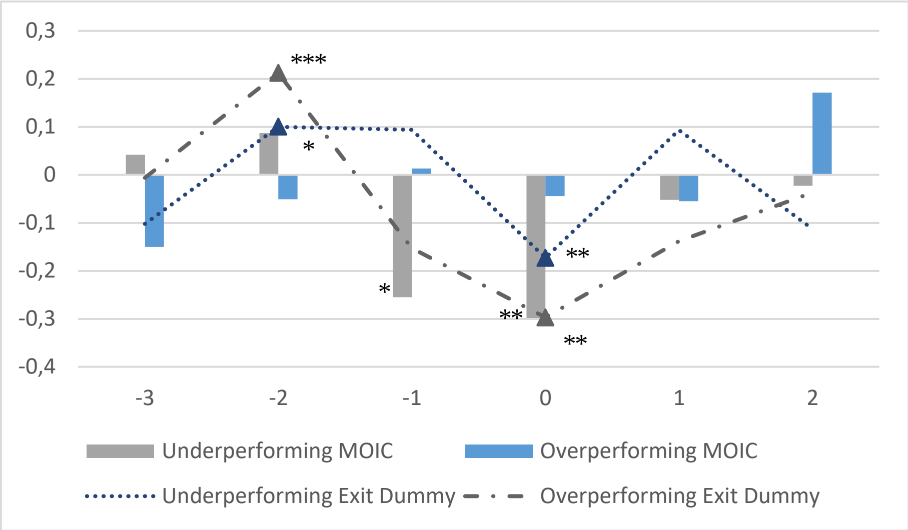
5.2.3 Dynamic Effects of Treatment Intensity at the Fund-Level

MOIC

The dynamic effects of busyness on exit performance (*MOIC*) reported in Table T.16 suggest that VC funds are only sufficiently distracted when they are primarily syndicating and lead-investing. The adverse effect of the industry shock is highest in *q* where a one percent increase in busyness decreases the *MOIC* by 0.298%. The coefficient is statistically significant at the 5% level. The effect, however, is also prevalent in *q-1*, albeit reduced in magnitude and statistical significance whereby a one percent increase in busyness decreases MOIC by 0.255%. The dynamics of the busyness effect are in line with the bias in later-quarter investments. The bias would imply that the effect would be greatest in *q*, given the 83-day lag in screening, but still prevalent in *q-1* given that a fraction of investments are spread across *q*. The fact that statistically and economically significant effects are only prevalent in lead-investing VC funds confirms our underlying hypothesis of the adverse effect of busyness since lead-investing is arguably the greatest indicator of the amount of time expended on individual ventures. With a higher average involvement of VC funds, we should therefore expectedly see a greater influence of industry shocks on VCs' re-allocation of time and subsequently a greater impact on VCs' ability to screen. We find no evidence to support nor reject hypothesis 2. The coefficients for primarily syndicating VC funds are negative and economically larger than those of non-syndicating VC funds which would suggest that syndication does not mitigate busyness. However, given that *D* is presumably not a valid measure of busyness on its own account, we have no way of knowing whether syndication actually exacerbates busyness. From a theoretical and empirical perspective (see Jääskeläinen, Maula, and Seppä, 2006) this would be highly unlikely.

Figure 4: Dynamic Effects of Syndicating, Lead-investing VC Funds

Dynamic effects of lagged and forward-looking measures of $log\ (D_{iq}^{IND} + 1)$ regressed on *log(MOIC+1)* and the exit dummy for *syndicate*=1, *leadinvestor*=1. . The x-axis represents the lag relative to the quarter of the investment. Standard errors are robust and clustered by VC fund. The y-axis represents the coefficient estimates. Controls including *syndicate* and fixed effects including *quarter* × *industry* FE are included.



To test whether the unobservable VC firm/fund characteristics and ability to withstand shocks are in fact correlated with *D*, we apply the Hausman test, where the null hypothesis is the random effects, and the alternative is the fixed effects (Roberts & Whited, 2013). With a *p*-value of < 0.000 we strongly reject the null confirming that endogeneity would be of concern in the random effects model (see Table T.17). The fixed effects specification is therefore appropriate in modeling the relationship of *D* and *MOIC.*

In Section 3.2 we argue that the added value of monitoring is presumably concentrated around the first investment rounds which means that the impact of *D* on *MOIC*, given compromised screening, may not be independent of the effect of monitoring, since, arguably, some level of economically meaningful variation is imposed on monitoring involvement. As an additional robustness test, we will therefore interact *D, syndicate*=1, *leadinvestor*=1 with the investment round. Table T.18 reports that the adverse effect of busyness on *MOIC* is in fact enhanced in later rounds and statistically significant in round 12 at the 1% level and in round 14 at the 5% level. The economic magnitude of the coefficients is substantially increased with a one percent increase in busyness decreasing *MOIC* by 3.3% in round 12, and 4% in round

14. With busyness being exogenous to the investment, these results would suggest that screening is more valuable in later rounds. With unobserved sorting being a primary determinant in value creation and unobservable characteristics having the tendency to subside over the life-cycle of the venture, this is a counterintuitive result. With later rounds minimizing the time between investment and exit, we may also explain the results by a smaller likelihood of the influence of unaccounted-for time-variant effects.

Exit Dummy

As for the *exit dummy*, we cannot identify any discernible pattern that would indicate that D × *syndicate* × *leadinvestor* represents a valid measure of busyness. Neither the signs of the coefficients nor the dynamic effects are in line with our predictions. Table T.16 reports both positive and negative statistically and economically significant coefficients for syndicating, lead-investing VC funds and dynamic effects that range from *q-2* to *q+2*. In the framework of the hypothesized adverse effect of busyness, we fail to explain why an industry shock in *q-2* in the portfolio of ventures unrelated to the investment would improve the likelihood of successful exit unless that shock freed up resources ex-post. This delay would, however, not be able to explain the positive statistically and economically significant effect of $log(D_{iq}^{IND-}+1)$, *syndicate*=0 *leadinvestor*=0 on the *exit dummy* given that the effect occurs in the investment's quarter. We can only surmise that there are underlying trends in the data that we cannot identify that drive invalid results in our regression. An observable problem, for example, is that - at the VC firm level - across the sample of investments, we observe an average *exit dummy* value of 0.9 indicating that 90% of ventures eventually went public or were acquired. Abuzov (2020), however, only reports a 23% likelihood of exit via acquisition or IPO. While we cannot be certain why our measure of D would be positively correlated with the prevalence of datapoints in Refinitiv Eikon, it provides some evidence of bias in the data. We would argue that, in light of results that largely align with predictions, *MOIC* does not carry the same bias given that more "realistic" variation is introduced in the sample. However, even *MOIC* would lack much of the true zero values that the data would contain if all non-successful exits would have been considered. In essence, if the *exit dummy* as an independent variable does not, in contrast to *MOIC*, capture bias in the data and both independent variables capture the same concept of financial success, we would have to conclude that both D and D × *syndicate* × *leadinvestor* are not valid measures of busyness because the results suggest relationships that are divergent from the theoretical and methodological framework developed. We could however argue that if both variables captured the same concept, we would expect the effect to be uniform in respect to the direction of coefficients, the dynamic effects, and the origin (underperforming vs. overperforming) as reported by Abuzov (2020) - which it is not. Distraction or busyness as a concept of value-destruction furthermore has a strong empirical and theoretical background (see e.g., Section 3.3), in particular in connection with VC-backed portfolio company outcomes (see Abuzov, 2020). However, IS_q^{IND} has not been used before in the context of venture capitalists and it might in fact not induce VCs to shift attention to a degree that is observable in the data. Similar to the higher likelihood of a consolidation of busy and non-busy investments at the VC firm level, we may also expect the same problem at the VC fund level. A solution to this problem would be to devise a measure of *D* that is specific to a VC partner that is known to have invested in a given venture.

6. Conclusion

In this paper we set out to determine whether venture capitalists can identify successful ventures ex-ante. To introduce variation to the otherwise unobservable screening involvement of VCs, we devise a firm-level proxy for distraction and find that at the VC firm-level, busyness only marginally affects future performance of portfolio companies. We ascribe the lack of economic magnitude to the misidentification of busy investments. In particular, VC firm-level distraction as a valid proxy is compromised as VC funds' restrictive covenants and industry specialization cause them to operate as separate entities whereby busy and non-busy investments are more likely consolidated. Close collaboration of VC partners at the VC fund-level allows us to measure busyness more precisely. However, we find that distraction induced by industry shocks and moderated in impact by the weight of the affected portfolio, is not sufficiently pronounced to impact portfolio company outcomes. To validate our results, we exploit heterogeneity in the treatment intensity by introducing variables that reinforce busyness and the impact of the industry shock. We find that busyness is especially severe when VC funds predominantly engage in lead investments arguably because lead investors are more likely to serve on boards and interact more frequently with ventures. However, we find no evidence to support the notion that syndication, as a means to distribute additional advice across co-investors, mitigates busyness. On the other hand, we neither accept the null hypothesis given that our proxy for distraction is likely not sufficiently pronounced to induce a mitigating effect of syndication.

Because the timing of screening is ultimately unobservable, we include lagged and forward-looking measures of busyness and find that busyness decreases the exit multiple in the quarter prior to investment and the investment's quarter by 0.255% and 0.298% for every 1% increase in our measure of distraction, respectively. Industry shocks preceding *q-1* and those that follow after the investment, on the other hand, do not affect investments. This pattern confirms the lag between the investment date and the timing of the screening process and matches the bias in the data of later-quarter investments. In contrast to the notion that busyness is value-destructive, we find that certain treatment combinations in fact increase the likelihood that a venture goes public or is acquired. Although busyness may be value-adding when venture capitalists engage in too much monitoring, we would then expect the positive effect of busyness to be more pronounced when VCs are primarily non-syndicating since over-monitoring is ex-ante mitigated by syndication. The results however predict a significantly higher positive busyness effect of syndicating VC funds. In addition to the fact that the signs of the coefficients and dynamic effects are divergent from predictions, we suggest that there are unobservable trends in the data that drive invalid results in the *exit dummy*. Given that the signs and economic magnitude of the busyness coefficients, the dynamic effects and the effect of treatment heterogeneity are mostly aligned with predictions, we argue that the effect of busyness on the exit multiple is a valid representation of the change in screening involvement and its adverse effect on VCs' ability to select successful ventures ex-ante. The results indicate that the significant returns generated by VCs are at least in part driven by VCs' ability to select successful ventures ex-ante that perform better ex-post. Our estimated coefficients provide an economic measure of the cost of distraction and the value of screening and may be utilized in VCs' process to decide on the optimal level of attention.

6.1 Limitations

Even though our paper's general premise is well rooted in theory and previous empirical research, the application of the various concepts linked together has not been undertaken in this particular manner. The most fundamental draw-back of the methodological approach in particular arises from the industry shock that has only so far been used in the context of institutional investors. There are theoretical arguments that support the industry shock as a measure of distraction, however we have no anecdotal or empirical evidence of its validity. The authors tried to reach out to venture capitalists on LinkedIn, however, unfortunately have received no responses.

Whilst w_q^{IND} provides an intuitive measure of the importance of a given industry shock, it may in fact not represent: one, the true financial importance given potentially changing intermittent exit valuations, and two, the actual time allocations of VC partners. w_q^{IND} thus, may or may not undermine the validity of our measure of distraction.

Limitations also arise from missing data in the form of unassignable exit dates. As dates are not values which are more easily estimated, an imputation would be a challenging process which the timeframe of this thesis did not give room for. Furthermore, the missing data could potentially have created a bias in our empirical model and therefore given us unexpected results.

6.2 Further Research

Further research might build upon the methodological model developed in this thesis and seek out anecdotal and/or empirical evidence on the validity of the measure of distraction. Furthermore, a potential way of improving and further research the topic of this thesis could be to implement the model on an individual VC partner level. This was not done in this thesis because, as mentioned, it would be a far more complex data allocation process which the timeframe of this thesis would not allow. Additionally, much of the data would also have been lost due to the complexity of the data allocation process which could have created problematic results. A potential problem with the firm level, however, is that VC firms often manage several active funds with numerous partners involved. However, only one partner is usually engaged within a portfolio company (Abuzov, 2020). An investment made by a VC firm which is deemed busy or distracted could therefore potentially have been made by a VC partner within the firm that in fact is not busy on an individual level. This could overstate the number of busy investments in the sample. We have taken this into consideration when creating our model by constructing a firm-level proxy of the distraction (see Section 4.2.1), but the issue could still be present. Therefore, could a model which is modified for the VC-partner level be an appropriate substitute to use in future research.

Tables

Table T.1: Summary Statistics

Table T.1 depicts the number of observations, standard deviation, mean, median, min and max values for the relevant variables of this thesis. The sample consists of 45 772 observations between 1999-2021 with both VC firms and portfolio companies being from the US.

Variables	Obs	Std. Dev.	Mean	Median	Min	Max
Distracted Dummy	45 772	.4506876	.2834702	0	0	1
D_{iq}^{IND-}	45 772	.0764047	.0207198	0	0	.9936428
D_{iq}^{IND+}	45 753	.076101	.0182553	0	0	.9974676
Lead Investor Dummy	45 753	.497105	.4462221	0	0	1
Stage Dummy	45 753	.4970455	.4456757	0	0	1
Syndicate Dummy	45 753	.4815098	.6347343	1	0	1
MOIC	45 772	28.10516	1.751201	0	0	3986.6
IPO/M&A Exit Dummy	45 772	.2836175	.9117801	1	0	1
Round Number	45 772	2.980458	4.001923	3	1	35
D_{iq}^{IND-} - 1	45 772	.0861507	.0218628	0	0	1
D_{iq}^{IND+} - 1	42 218	.0846142	.0200787	0	0	1
D_{iq}^{IND-} - 2	45 772	.0813877	.0199722	0	0	1
D_{iq}^{IND+} - 2	40 885	.0870077	.0209713	0	0	1
D_{iq}^{IND-} - 3	39 382	.0860048	.0223808	0	0	1
D_{iq}^{IND+} - 3	39 417	.0863556	.02031	0	0	1
D_{iq}^{IND-} + 1	45 680	.0784926	.0213235	0	0	1
D_{iq}^{IND+} + 1	45 681	.0765942	.0184153	0	0	.9943502
D_{iq}^{IND-} + 2	45 506	.0801386	.0220573	0	0	1
D_{iq}^{IND+} + 2	45 509	.0777014	.0191872	0	0	1

Table T.2: Descriptive Statistics for Distracted and Non-Distracted Investments

Table T.2 shows the mean, median, min and max values for the distracted and non-distracted investments. The table also depict the differences between the mean and median for the two clusters. The total values are also shown.

Distraction		D_{iq}^{IND-}	D_{iq}^{IND+}	Lead Investor Dummy	Stage Dummy	Syndicate Dummy	MOIC	IPO/M&A Exit Dummy	Round Number
Non-Distracted	Obs	32797	32797	32797	32797	32797	32797	32797	32797
	Mean	0	0	.4304052	.4469921	.6390828	1.803208	.9131018	4.015581
	Median	0	0	0	0	1	.0108634	1	3
	Min	0	0	0	0	0	0	0	1
	Max	0	0	1	1	1	1400	1	35
Distracted	Obs	12975	12956	12956	12956	12975	12975	12975	12975
	Mean	.0730936	.0644669	.4862612	.4423433	.6237265	1.619743	.9084393	3.967399
	Median	.0141709	.0048298	0	0	1	0	1	3
	Min	0	0	0	0	0	0	0	1
	Max	.9936428	.9974676	1	1	1	3986.6	1	31
Difference (Distracted – Non Distracted)	Mean	.0730936	.0644669	.055856	-.0046488	-.0153563	-.183465	-.0046625	-.048182
	Median	.0141709	.0048298	0	0	0	-.0108634	0	0
Total	Obs	45772	45753	45753	45753	45753	45772	45772	45772
	Mean	.0207198	.0182553	.4462221	.4456757	.6347343	1.751201	.9117801	4.001923
	Median	0	0	0	0	1	0	1	3
	Min	0	0	0	0	0	0	0	1
	Max	.9936428	.9974676	1	1	1	3986.6	1	35

Table T.3: Industry Clustered Descriptive Statistics

Table T.3 shows the number of observations, mean, median, min and max of all the 10 GICS industry sectors.

Industries (GICS)		D_{iq}^{IND-}	D_{iq}^{IND+}	Lead Investor Dummy	Stage Dummy	Syndicate Dummy	MOIC	IPO/M&A Exit Dummy	Round Number
Health Care	Obs	13311	13292	13292	13292	13292	13311	13311	13311
	Mean	.008815	.0053231	.4097954	.418372	.6744658	1.483768	.9191646	4.535196
	Median	0	0	0	0	1	.1611678	1	4
	Min	0	0	0	0	0	0	0	1
	Max	.8016154	.7775654	1	1	1	1400	1	35
Consumer Discretionary	Obs	1816	1816	1816	1816	1816	1816	1816	1816
	Mean	.0286087	.0215714	.4625551	.4471366	.6007709	1.424658	.8882159	3.420705
	Median	0	0	0	0	1	0	1	3
	Min	0	0	0	0	0	0	0	1
	Max	.9128453	.9834022	1	1	1	315.0241	1	17
Communication Services	Obs	3389	3389	3389	3389	3389	3389	3389	3389
	Mean	.0068824	.0104847	.4544113	.5057539	.6169962	1.951239	.9132487	4.234582
	Median	0	0	0	1	1	0	1	3
	Min	0	0	0	0	0	0	0	1
	Max	.574638	.7291682	1	1	1	727.2727	1	20
Information Technology	Obs	23531	23531	23531	23531	23531	23531	23531	23531
	Mean	.0274664	.0251281	.4581616	.4456249	.629085	1.610268	.9134758	3.761166
	Median	0	0	0	0	1	0	1	3
	Min	0	0	0	0	0	0	0	1
	Max	.9864713	.9974676	1	1	1	1388.889	1	25
Industrials	Obs	2257	2257	2257	2257	2257	2257	2257	2257
	Mean	.032564	.024812	.5002215	.5006646	.5587062	1.761691	.9144883	3.77891
	Median	0	0	1	1	1	0	1	3
	Min	0	0	0	0	0	0	0	1
	Max	.9936428	.9634265	1	1	1	990.5	1	24
Consumer Staples	Obs	351	351	351	351	351	351	351	351
	Mean	.0344224	.0274107	.4871795	.4985755	.5128205	8.009842	.8005698	3.752137
	Median	0	0	0	0	1	0	1	3
	Min	0	0	0	0	0	0	0	1
	Max	.9768344	.95186	1	1	1	591.4972	1	12
Financials	Obs	673	673	673	673	673	673	673	673
	Mean	.0223249	.0203131	.4249629	.4457652	.5958395	8.575331	.9004458	3.490342
	Median	0	0	0	0	1	.1949803	1	3
	Min	0	0	0	0	0	0	0	1

	Max	.9025788	.9330027	1	1	1	3986.6	1	13
Materials	Obs	197	197	197	197	197	197	197	197
	Mean	.0178017	.0487069	.5076142	.3908629	.4873096	1.721262	.7614213	3.050761
	Median	0	0	1	0	0	0	1	2
	Min	0	0	0	0	0	0	0	1
	Max	.5646818	.9905335	1	1	1	75.61538	1	10
Energy	Obs	185	185	185	185	185	185	185	185
	Mean	.0182473	.037304	.5297297	.572973	.6162162	2.182264	.7621622	3.92973
	Median	0	0	1	1	1	.2250205	1	3
	Min	0	0	0	0	0	0	0	1
	Max	.6106886	.8963553	1	1	1	64.66416	1	16
Utilities	Obs	62	62	62	62	62	62	62	62
	Mean	.0296741	.0434211	.3870968	.483871	.6290323	.2061422	.8709677	3.516129
	Median	0	0	0	0	1	0	1	4
	Min	0	0	0	0	0	0	0	1
	Max	.7086675	.4375622	1	1	1	3.504803	1	9

Table T.4: Frequency of Distractions in All Relevant Years

Table T.4 show the frequency of distracted investments in relation to the total number of distracted investments and non-distracted investments in relation to the total number of non-distracted investments for each year as well as all the investments made during a year in relation to all investments. The data is shown both with absolute numbers and percentages.

	Non-Distracted		Distracted		All	
Year	**Frequency**	**Percent**	**Frequency**	**Percent**	**Frequency**	**Percent**
1999	1955	5,96%	71	0,55%	2026	4,43%
2000	2669	8,13%	1780	13,74%	4449	9,72%
2001	2028	6,18%	652	5,03%	2680	5,86%
2002	1072	3,27%	912	7,04%	1984	4,33%
2003	1530	4,66%	695	5,36%	2225	4,86%
2004	1777	5,42%	1103	8,51%	2880	6,29%
2005	2630	8,01%	457	3,53%	3087	6,74%
2006	2388	7,28%	691	5,33%	3079	6,73%
2007	2374	7,23%	1035	7,99%	3409	7,45%
2008	2166	6,60%	882	6,81%	3048	6,66%
2009	1674	5,10%	381	2,94%	2055	4,49%
2010	1565	4,77%	591	4,56%	2156	4,71%
2011	1530	4,66%	751	5,80%	2281	4,98%
2012	1322	4,03%	622	4,80%	1944	4,25%
2013	1155	3,52%	739	5,70%	1894	4,14%
2014	1311	4,00%	478	3,69%	1789	3,91%
2015	1215	3,70%	369	2,85%	1584	3,46%
2016	592	1,80%	253	1,95%	845	1,85%
2017	632	1,93%	233	1,80%	865	1,89%
2018	611	1,86%	114	0,88%	725	1,58%
2019	293	0,89%	115	0,89%	408	0,89%
2020	308	0,94%	32	0,25%	340	0,74%
2021	19	0,06%	0	0,00%	19	0,04%
Total	32816	100,00%	12956	100,00%	45772	100,00%

Table T.5: Summary Statistics Fund-Level

Table T.5 depicts the number of observations, standard deviation, mean, median, min and max values for the relevant variables of this thesis. The sample consists of 31 514 observations between 1999-2021 with both VC funds and portfolio companies being from the US.

Variables	Obs	Std. Dev.	Mean	Median	Min	Max
Distracted Dummy	31 514	.3382597	.1317827	0	0	1
D_{iq}^{IND-}	31 509	.0779262	.0157435	0	0	.9761415
D_{iq}^{IND+}	31 509	.0669168	.0112802	0	0	.9851872
Lead Investor Dummy	31 509	.4984705	.4608207	0	0	1
Stage Dummy	31 509	.496236	.4387001	0	0	1
Syndicate Dummy	31 509	.4927066	.5851344	1	0	1
MOIC	31 514	39.42126	2.717649	.0075634	0	3380.952
IPO/M&A Exit Dummy	31 514	.2941016	.90436	1	0	1
Round Number	31 514	2.981833	4.150378	4	1	34
D_{iq}^{IND-} - 1	26 436	.0993394	.0207321	0	0	1
D_{iq}^{IND+} - 1	26 461	.0821771	.0139376	0	0	1
D_{iq}^{IND-} - 2	24 907	.0987554	.0198947	0	0	1
D_{iq}^{IND+} - 2	24 927	.0819669	.0145192	0	0	1
D_{iq}^{IND-} - 3	23 387	.0974968	.0197679	0	0	1
D_{iq}^{IND+} - 3	23 441	.0833551	.0138697	0	0	1
D_{iq}^{IND-} + 1	31 475	.0806165	.0169736	0	0	1
D_{iq}^{IND+} + 1	31 479	.0696972	.0120508	0	0	1
D_{iq}^{IND-} + 2	31 361	.0834479	.0179624	0	0	1
D_{iq}^{IND+} + 2	31 364	.0731082	.013102	0	0	1

Table T.6: Descriptive Statistic for Distracted and Non-Distracted Investments Fund-Level

Table T.6 shows the mean, median, min and max values for the distracted and non-distracted investments. The table also depict the differences between the mean and median for the two clusters. The total values are also shown.

Distraction		D_{iq}^{IND-}	D_{iq}^{IND+}	Lead Investor Dummy	Stage Dummy	Syndicate Dummy	MOIC	IPO/M&A Exit Dummy	Round Number
Non-Distracted	Obs	27361	27361	27361	27361	27361	27361	27361	27361
	Mean	0	0	.454881	.4392749	.5982603	2.835926	.9052666	4.166039
	Median	0	0	0	0	1	.025337	1	4
	Min	0	0	0	0	0	0	0	1
	Max	0	0	1	1	1	3380.952	1	34
Distracted	Obs	4148	4148	4148	4148	4148	4153	4153	4153
	Mean	.1195908	.0856866	.500000	.4349084	.4985535	1.938416	.8983867	4.047195
	Median	.0340093	0	.500000	0	0	0	1	3
	Min	0	0	0	0	0	0	0	1
	Max	.9761415	.9851872	1	1	1	607.4222	1	24
Difference (Distracted – Non Distracted)	Mean	.1195908	.0856866	.045119	-.0043665	-.0997068	-.89751	-0.0068799	-.118844
	Median	.0340093	0	.500000	0	-1	-.025337	0	-1
Total	Obs	31509	31509	31509	31509	31509	31514	31514	31514
	Mean	.0157435	.0112802	.4608207	.4387001	.5851344	2.717649	.90436	4.150378
	Median	0	0	0	0	1	.0075634	1	4
	Min	0	0	0	0	0	0	0	1
	Max	.9761415	.9851872	1	1	1	3380.952	1	34

Table T.7: Industry Clustered Descriptive Statistics Fund-Level

Table T.7 shows the number of observations, mean, median, min and max of all the 10 GICS industry sectors.

Industries (GICS)		D_{iq}^{IND-}	D_{iq}^{IND+}	Lead Investor Dummy	Stage Dummy	Syndicate Dummy	MOIC	IPO/M&A Exit Dummy	Round Number
Health Care	Obs	9958	9958	9958	9958	9958	9963	9963	9963
	Mean	.005153	.0027668	.4036955	.3793935	.6839727	2.496182	.9170932	4.561176
	Median	0	0	0	0	1	.2082529	1	4
	Min	0	0	0	0	0	0	0	1
	Max	.944961	.9617327	1	1	1	3333.333	1	34
Consumer Discretionary	Obs	1207	1207	1207	1207	1207	1207	1207	1207
	Mean	.0191926	.012365	.4987572	.4614747	.5120133	2.175562	.8690969	3.721624
	Median	0	0	0	0	1	0	1	3
	Min	0	0	0	0	0	0	0	1
	Max	.9729958	.9851872	1	1	1	315.0241	1	17
Communication Services	Obs	2436	2436	2436	2436	2436	2436	2436	2436
	Mean	.0052669	.0060599	.4499179	.5188834	.5706076	3.001863	.9022989	4.241379
	Median	0	0	0	1	1	0	1	3
	Min	0	0	0	0	0	0	0	1
	Max	.8456764	.6307577	1	1	1	727.2727	1	20
Information Technology	Obs	15426	15426	15426	15426	15426	15426	15426	15426
	Mean	.0227327	.0161748	.486257	.4535849	.5403864	2.499301	.9032802	3.957085
	Median	0	0	0	0	1	0	1	3
	Min	0	0	0	0	0	0	0	1
	Max	.9729958	.9844279	1	1	1	2208.333	1	25
Industrials	Obs	1532	1532	1532	1532	1532	1532	1532	1532
	Mean	.0262183	.0175976	.5104439	.4934726	.520235	4.555157	.9060052	3.839426
	Median	0	0	1	0	1	0	1	3
	Min	0	0	0	0	0	0	0	1
	Max	.9761415	.9642196	1	1	1	3380.952	1	24
Consumer Staples	Obs	265	265	265	265	265	265	265	265
	Mean	.0274015	.0278184	.5811321	.4603774	.4679245	10.23266	.7773585	4.166038
	Median	0	0	1	0	0	0	1	4
	Min	0	0	0	0	0	0	0	1
	Max	.7687659	.8569394	1	1	1	591.4972	1	12
Financials	Obs	420	420	420	420	420	420	420	420
	Mean	.0187063	.015329	5380952	.4904762	.5214286	4.890239	.9071429	3.569048
	Median	0	0	1	0	1	.25185	1	3
	Min	0	0	0	0	0	0	0	1
	Max	.9025788	.7374846	1	1	1	407.4074	1	13

Materials	Obs	117	117	117	117	117	117	117	117
	Mean	.0114751	.0251077	.5470085	.4188034	.4017094	2.443115	.7350427	3.111111
	Median	0	0	1	0	0	0	1	2
	Min	0	0	0	0	0	0	0	1
	Max	.5516702	.9694038	1	1	1	86.95652	1	10
Energy	Obs	124	124	124	124	124	124	124	124
	Mean	.0114171	.0282793	.5080645	.6451613	.6693548	1.987944	.8387097	4.25
	Median	0	0	1	1	1	.2539295	1	4
	Min	0	0	0	0	0	0	0	1
	Max	.5940347	.9148691	1	1	1	48.00307	1	16
Utilities	Obs	24	24	24	24	24	24	24	24
	Mean	.0014685	.0609422	.500000	.5833333	.50000	.2280577	.7083333	4.583333
	Median	0	0	.500000	1	.500000	0	1	5
	Min	0	0	0	0	0	0	0	1
	Max	.0352435	.4287346	1	1	1	1.094677	1	9

Table T.8: Frequency of Distractions in All Relevant Years Fund-Level

Table T.8 show the frequency of distracted investments in relation to the total number of distracted investments and non-distracted investments in relation to the total number of non-distracted investments for each year as well as all the investments made during a year in relation to all investments. The data is shown both with absolute numbers and percentages.

	Non-Distracted		Distracted		All	
Year	**Frequency**	**Percent**	**Frequency**	**Percent**	**Frequency**	**Percent**
1999	1485	5,43%	1	0,02%	1486	4,72%
2000	2582	9,43%	609	14,68%	3191	10,13%
2001	1869	6,83%	263	6,34%	2132	6,77%
2002	1131	4,13%	357	8,61%	1488	4,72%
2003	1418	5,18%	250	6,03%	1668	5,29%
2004	1732	6,33%	482	11,62%	2214	7,03%
2005	2262	8,27%	201	4,85%	2463	7,82%
2006	2128	7,78%	317	7,64%	2445	7,76%
2007	2238	8,18%	414	9,98%	2652	8,42%
2008	2148	7,85%	291	7,02%	2439	7,74%
2009	1466	5,36%	81	1,95%	1547	4,91%
2010	1285	4,70%	161	3,88%	1446	4,59%
2011	1215	4,44%	164	3,95%	1379	4,38%
2012	934	3,41%	155	3,74%	1089	3,46%
2013	907	3,31%	146	3,52%	1053	3,34%
2014	809	2,96%	107	2,58%	916	2,91%
2015	669	2,44%	63	1,52%	732	2,32%
2016	307	1,12%	40	0,96%	347	1,10%
2017	327	1,19%	28	0,68%	355	1,13%
2018	258	0,94%	6	0,14%	264	0,84%
2019	108	0,39%	12	0,29%	120	0,38%
2020	84	0,31%	0	0,00%	84	0,27%
2021	5	0,02%	0	0,00%	5	0,02%
Total	27367	100,00%	4148	100,00%	31515	100,00%

Table T.9: Baseline Regression Results

Main regression results for $log(D_{iq}^{IND-}+1)$ and $log(D_{iq}^{IND+}+1)$ regressed on log(MOIC+1) and the indicator variable equal to 1 if a venture was acquired or went public. Controls comprise the amount raised in a given round, the round number, the size of the syndicate, and the total funds raised by a given venture prior to the assigned exit date. Regression was conducted using fixed effects estimation, with standard errors clustered by the VC. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1 denote the statistical significance.

	log(MOIC+1)			*Exit Dummy*		
	(1)	(2)	(3)	(4)	(5)	(6)
	FE	FE	FE, clustered robust	FE	FE	FE, clustered robust
$log(D_{iq}^{IND-}+1)$	0.031	0.020	0.020	-0.060***	-0.060***	-0.060**
	(0.043)	(0.042)	(0.042)	(0.022)	(0.022)	(0.025)
$log(D_{iq}^{IND+}+1)$	0.077*	0.065	0.065	-0.046**	-0.045**	-0.045**
	(0.043)	(0.042)	(0.049)	(0.022)	(0.022)	(0.022)
Controls	No	Yes	Yes	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
VC Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.090	0.306***	0.306***	0.928***	0.928***	0.928***
	(0.082)	(0.082)	(0.077)	(0.043)	(0.044)	(0.060)
Observations	45,297	45,297	45,297	45,753	45,753	45,753
R-squared	0.008	0.036	0.036	0.020	0.021	0.021
Number of VCID	3,413	3,413	3,413	3,434	3,434	3,434

Table T.10: Baseline Regression Lagged and Forward-looking Measures of D

Regression results for lagged and forward-looking measures of $log(D_{iq}^{IND-}+1)$ and $log(D_{iq}^{IND+}+1)$ regressed on *log(MOIC+1)* and the indicator variable equal to 1 if a venture was acquired or went public. Controls comprise the amount raised in a given round, the round number, the size of the syndicate, and the total funds raised by a given venture prior to the assigned exit date. Regression was conducted using fixed effects estimation, with standard errors clustered by the VC firm. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1 denote the statistical significance.

	Log(MOIC+1)		*Exit Dummy*	
	(1)	(2)	(3)	(4)
	G	H	J	K
$\boldsymbol{log(D_{iq}^{IND-}+1)}$	0.013	0.013	-0.046*	-0.046*
	(0.047)	(0.047)	(0.024)	(0.025)
D(-1)	-0.039	-0.039	0.016	0.016
	(0.043)	(0.043)	(0.022)	(0.027)
D(-2)	-0.122***	-0.122***	-0.043*	-0.043*
	(0.044)	(0.046)	(0.022)	(0.025)
D(-3)	0.061	0.061	-0.029	-0.029
	(0.044)	(0.048)	(0.022)	(0.027)
D(+1)	0.039	0.039	0.019	0.019
	(0.048)	(0.050)	(0.024)	(0.025)
D(+2)	0.071	0.071	-0.038	-0.038
	(0.051)	(0.057)	(0.025)	(0.030)
$\boldsymbol{log(D_{iq}^{IND+}+1)}$	0.016	0.016	-0.052**	-0.052**
	(0.047)	(0.051)	(0.023)	(0.022)
D(-1)	0.033	0.033	-0.008	-0.008
	(0.043)	(0.050)	(0.021)	(0.020)
D(-2)	-0.023	-0.023	0.007	0.007
	(0.042)	(0.048)	(0.021)	(0.022)
D(-3)	0.020	0.020	-0.026	-0.026
	(0.044)	(0.046)	(0.022)	(0.023)
D(+1)	-0.057	-0.057	-0.046**	-0.046**
	(0.047)	(0.052)	(0.023)	(0.022)
D(+2)	-0.036	-0.036	0.014	0.014
	(0.046)	(0.051)	(0.023)	(0.022)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
VC Firm FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Constant	0.244***	0.244***	0.958***	0.958***
	(0.095)	(0.081)	(0.047)	(0.065)
Observations	38,727	38,727	38,961	38,961
R-squared	0.040	0.040	0.020	0.020
Number of VCID	2,298	2,298	2,303	2,303

Table T.11: VC Fund-Level Regression Results

Fund-level results for D_{iq}^{IND-} and D_{iq}^{IND+} regressed on *log(MOIC+1)* and the indicator variable equal to 1 if a venture was acquired or went public. Controls comprise the amount raised in a given round, the round number, the size of the syndicate, and the total funds raised by a given venture prior to the assigned exit date. Regression was conducted using fixed effects estimation, with standard errors clustered by the VC fund. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1 denote the statistical significance.

	log(MOIC+1)			*Exit Dummy*		
	FE	FE	FE, clustered robust	FE	FE	FE, clustered robust
$log\ (D_{iq}^{IND-}+1)$	-0.031	-0.075	-0.075	-0.036	-0.035	-0.035
	(0.060)	(0.059)	(0.063)	(0.028)	(0.028)	(0.031)
$log(D_{iq}^{IND+}+1)$	0.057	0.052	0.052	-0.057*	-0.054*	-0.054
	(0.068)	(0.067)	(0.075)	(0.032)	(0.032)	(0.033)
Constant	0.363**	0.553***	0.553***	0.800***	0.790***	0.790***
	(0.183)	(0.181)	(0.152)	(0.086)	(0.087)	(0.099)
Controls	No	Yes	Yes	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
VC Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	31,194	31,194	31,194	31,509	31,509	31,509
R-squared	0.009	0.040	0.040	0.011	0.012	0.012
Number of FundID	4,479	4,479	4,479	4,517	4,517	4,517

Table T.12: VC Fund-Level Regression - Lagged and Forward-looking Measures of D

Regression results for lagged and forward-looking measures of $log(D_{iq}^{IND-}+1)$ and $log(D_{iq}^{IND+}+1)$ regressed on *log(MOIC+1)* and the indicator variable equal to 1 if a venture was acquired or went public. Controls comprise the amount raised in a given round, the round number, the size of the syndicate, and the total funds raised by a given venture prior to the assigned exit date. Regression was conducted using fixed effects estimation, with standard errors clustered by the VC fund. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1 denote the statistical significance.

	log(MOIC+1)		*Exit Dummy*	
	(1)	(2)	(3)	(4)
	FE,	FE, clustered robust	FE	FE, clustered robust
$\boldsymbol{log(D_{iq}^{IND-}+1)}$	-0.081	-0.081	-0.052	-0.052
	(0.069)	(0.071)	(0.032)	(0.034)
D(-1)	-0.089	-0.089	0.054*	0.054*
	(0.060)	(0.062)	(0.028)	(0.031)
D(-2)	-0.078	-0.078	-0.030	-0.030
	(0.059)	(0.063)	(0.028)	(0.032)
D(-3)	0.101*	0.101	-0.022	-0.022
	(0.059)	(0.068)	(0.028)	(0.030)
D(+1)	-0.053	-0.053	0.057*	0.057*
	(0.068)	(0.071)	(0.032)	(0.031)
D(+2)	0.008	0.008	-0.045	-0.045
	(0.073)	(0.074)	(0.034)	(0.035)
$\boldsymbol{log(D_{iq}^{IND+}+1)}$	-0.015	-0.015	-0.069**	-0.069**
	(0.073)	(0.082)	(0.034)	(0.035)
D(-1)	0.138**	0.138	0.002	0.002
	(0.067)	(0.084)	(0.031)	(0.028)
D(-2)	-0.021	-0.021	0.018	0.018
	(0.065)	(0.069)	(0.030)	(0.035)
D(-3)	-0.004	-0.004	-0.018	-0.018
	(0.068)	(0.076)	(0.032)	(0.036)
D(+1)	-0.156**	-0.156*	-0.033	-0.033
	(0.071)	(0.087)	(0.033)	(0.033)
D(+2)	-0.000	-0.000	-0.030	-0.030
	(0.069)	(0.080)	(0.032)	(0.033)
Constant	0.389*	0.389**	0.875***	0.875***
	(0.231)	(0.190)	(0.109)	(0.082)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
VC Fund FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	22,907	22,907	23,081	23,081
R-squared	0.041	0.041	0.015	0.015
Number of FundID	2,774	2,774	2,782	2,782

Table *T.13*: Treatment Intensity at the Fund-Level

Regression results for combinations of $log(D_{iq}^{IND-}+1)$ and $log(D_{iq}^{IND+}+1)$ with the dummy variables *syndicate* and leadinvestor regressed on *log(MOIC+1)* and the indicator variable equal to 1 if a venture was acquired or went public. Controls comprise the amount raised in a given round, the round number, the size of the syndicate, and the total funds raised by a given venture prior to the assigned exit date. Regression was conducted using fixed effects estimation, with standard errors clustered by the VC fund. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1 denote the statistical significance.

VARIABLES	*Syndicate*	*Leadinvestor*	(1) FE, clustered robust *logMOIC*	(2) FE, clustered robust *Exit Dummy*
$\boldsymbol{ln\ (D_{iq}^{IND-}+1)}$	0	0	-0.054	0.120**
			(0.127)	(0.059)
	0	1	0.024	0.008
			(0.120)	(0.047)
	1	0	-0.105	-0.122**
			(0.098)	(0.055)
	1	1	-0.227*	-0.047
			(0.128)	(0.086)
$\boldsymbol{ln\ (D_{iq}^{IND+}+1)}$	0	0	0.026	0.020
			(0.171)	(0.076)
	0	1	-0.018	-0.042
			(0.138)	(0.051)
	1	0	0.169	-0.035
			(0.119)	(0.060)
	1	1	-0.008	-0.229**
			(0.166)	(0.107)
Controls			Yes	Yes
Year FE			Yes	Yes
Quarter FE			Yes	Yes
VC Fund FE			Yes	Yes
Industry FE			Yes	Yes
Constant			0.555***	0.790***
			(0.152)	(0.100)
Observations			31,194	31,509
R-squared			0.040	0.012
Number of FundID			4,479	4,517

Table *T.14*: Treatment Intensity at the Fund-Level – Additional Controls

Regression results for combinations of $log(D_{iq}^{IND-}+1)$ and $log(D_{iq}^{IND+}+1)$ with the dummy variables *syndicate* and *leadinvestor* regressed on *log(MOIC+1)* and the indicator variable equal to 1 if a venture was acquired or went public. Controls comprise *syndicate*, the amount raised in a given round, the round number, the size of the syndicate, and the total funds raised by a given venture prior to the assigned exit date. Regression was conducted using fixed effects estimation (including *quarter* × *industry* FE), with standard errors clustered by the VC fund. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1 denote the statistical significance.

			log(MOIC+1)		*Exit Dummy*	
			(1)	(2)	(3)	(4)
	Syndicate	*Leadinvestor*	FE, clustered robust	FE, clustered robust	FE, clustered robust	FE, clustered robust
$\boldsymbol{log(D_{iq}^{IND-}+1)}$	0	0	-0.025	-0.024	0.116**	0.109*
			(0.130)	(0.130)	(0.059)	(0.058)
	0	1	0.037	0.039	0.007	-0.001
			(0.120)	(0.120)	(0.047)	(0.047)
	1	0	-0.117	-0.118	-0.120**	-0.119**
			(0.098)	(0.098)	(0.055)	(0.055)
	1	1	-0.246*	-0.239*	-0.045	-0.041
			(0.128)	(0.127)	(0.085)	(0.084)
$\boldsymbol{log(D_{iq}^{IND+}+1)}$	0	0	0.046	0.043	0.018	0.008
			(0.171)	(0.170)	(0.076)	(0.076)
	0	1	-0.005	0.002	-0.043	-0.052
			(0.139)	(0.139)	(0.051)	(0.051)
	1	0	0.158	0.168	-0.034	-0.034
			(0.119)	(0.120)	(0.060)	(0.060)
	1	1	-0.027	-0.014	-0.227**	-0.234**
			(0.164)	(0.164)	(0.107)	(0.110)
Syndicate			0.022*	0.022*	-0.003	-0.004
			(0.012)	(0.012)	(0.007)	(0.007)
Controls			Yes	Yes	Yes	Yes
Year FE			Yes	Yes	Yes	Yes
Quarter FE			Yes	Yes	Yes	Yes
VC Fund FE			Yes	Yes	Yes	Yes
Industry FE			Yes	Yes	Yes	Yes
Quarter × Industry FE			No	Yes	No	Yes
Constant			0.539***	0.408***	0.792***	0.629***
			(0.152)	(0.103)	(0.100)	(0.116)
Observations			31,194	31,194	31,509	31,509
R-squared			0.040	0.042	0.012	0.015
Number of FundID			4,479	4,479	4,517	4,517

Table *T.15*: Treatment Intensity at the Fund-Level – Additional Controls & Interactions

				log(MOIC+1)		*Exit Dummy*	
	Synd-icate	*Lead-investor*	*Stage*	(1) FE, clustered robust	(2) FE, clustered robust	(3) FE, clustered robust	(4) FE, clustered robust
$log(D_{iq}^{IND-}+1)$	0	0	0	0.007	0.000	0.213***	0.200**
				(0.192)	(0.194)	(0.078)	(0.079)
	0	0	1	-0.057	-0.050	0.036	0.033
				(0.169)	(0.167)	(0.085)	(0.083)
	0	1	0	0.127	0.126	0.056	0.049
				(0.140)	(0.141)	(0.052)	(0.052)
	0	1	1	-0.194	-0.183	-0.123	-0.134
				(0.209)	(0.210)	(0.094)	(0.094)
	1	0	0	-0.211	-0.211	-0.186*	-0.182*
				(0.175)	(0.177)	(0.105)	(0.105)
	1	0	1	-0.079	-0.080	-0.093	-0.092
				(0.114)	(0.114)	(0.060)	(0.061)
	1	1	0	-0.299**	-0.293**	-0.077	-0.079
				(0.136)	(0.137)	(0.103)	(0.103)
	1	1	1	-0.205	-0.195	-0.017	-0.007
				(0.205)	(0.203)	(0.133)	(0.130)
$log(D_{iq}^{IND+}+1)$	0	0	0	-0.113	-0.118	-0.041	-0.060
				(0.219)	(0.217)	(0.100)	(0.099)
	0	0	1	0.166	0.165	0.065	0.062
				(0.247)	(0.244)	(0.107)	(0.109)
	0	1	0	-0.100	-0.093	-0.115*	-0.128**
				(0.161)	(0.162)	(0.060)	(0.059)
	0	1	1	0.269	0.276	0.161**	0.165**
				(0.251)	(0.253)	(0.072)	(0.072)
	1	0	0	0.140	0.148	-0.055	-0.057
				(0.183)	(0.183)	(0.097)	(0.098)
	1	0	1	0.172	0.184	-0.017	-0.016
				(0.154)	(0.155)	(0.075)	(0.076)
	1	1	0	-0.015	-0.005	-0.242	-0.257*
				(0.178)	(0.177)	(0.152)	(0.156)
	1	1	1	-0.043	-0.027	-0.210	-0.208
				(0.300)	(0.300)	(0.148)	(0.152)
Controls				Yes	Yes	Yes	Yes
Year FE				Yes	Yes	Yes	Yes
Quarter FE				Yes	Yes	Yes	Yes
VC Fund FE				Yes	Yes	Yes	Yes
Industry FE				Yes	Yes	Yes	Yes
Quarter x Industry FE				No	Yes	No	Yes
Constant				0.530***	0.389***	0.790***	0.624***
				(0.152)	(0.103)	(0.100)	(0.116)
Observations				31,194	31,194	31,509	31,509
R-squared				0.040	0.042	0.013	0.015
Number of FundID				4,479	4,479	4,517	4,517

Table *T.16*: Dynamic Effects of Treatment Intensity at the Fund-Level

VARIABLES	*Synd-icate*	*Lead-investor*	(1) FE, clustered robust *logMOIC*	(2) FE, clustered robust *logMOIC*	(3) FE, clustered robust *Exit Dummy*	(4) FE, clustered robust *Exit Dummy*
$\boldsymbol{log(D_{iq}^{IND-}+1)}$	0	0	-0.109	-0.098	0.169**	0.163**
			(0.176)	(0.177)	(0.068)	(0.069)
	0	1	0.130	0.141	-0.052	-0.052
			(0.136)	(0.136)	(0.051)	(0.051)
	1	0	-0.166	-0.163	-0.078	-0.071
			(0.105)	(0.106)	(0.060)	(0.060)
	1	1	-0.326**	-0.298**	-0.190**	-0.173**
			(0.139)	(0.139)	(0.088)	(0.087)
D(-1)	0	0	0.055	0.051	-0.018	-0.011
			(0.165)	(0.164)	(0.079)	(0.080)
	0	1	-0.079	-0.096	0.108**	0.109**
			(0.117)	(0.116)	(0.042)	(0.043)
	1	0	-0.087	-0.096	0.016	0.017
			(0.086)	(0.086)	(0.055)	(0.055)
	1	1	-0.253*	-0.255*	0.094	0.094
			(0.147)	(0.146)	(0.084)	(0.085)
D(-2)	0	0	0.100	0.105	-0.051	-0.041
			(0.183)	(0.182)	(0.088)	(0.089)
	0	1	-0.151	-0.141	0.050	0.049
			(0.126)	(0.128)	(0.048)	(0.048)
	1	0	-0.139	-0.136	-0.151***	-0.145**
			(0.087)	(0.087)	(0.056)	(0.057)
	1	1	0.086	0.087	0.097*	0.100*
			(0.127)	(0.127)	(0.058)	(0.057)
D(-3)	0	0	-0.030	-0.028	-0.036	-0.035
			(0.169)	(0.168)	(0.081)	(0.080)
	0	1	0.223	0.224	-0.012	-0.015
			(0.142)	(0.142)	(0.036)	(0.036)
	1	0	0.029	0.028	-0.008	-0.010
			(0.076)	(0.076)	(0.055)	(0.056)
	1	1	0.043	0.042	-0.095	-0.102
			(0.147)	(0.148)	(0.091)	(0.092)
D(+1)	0	0	-0.260	-0.266	0.113*	0.112*
			(0.172)	(0.173)	(0.065)	(0.064)
	0	1	-0.043	-0.048	0.046	0.044
			(0.132)	(0.132)	(0.044)	(0.043)
	1	0	0.001	-0.001	0.024	0.019
			(0.103)	(0.103)	(0.055)	(0.055)
	1	1	-0.032	-0.052	0.112	0.093
			(0.146)	(0.143)	(0.070)	(0.069)
D(+2)	0	0	-0.241	-0.229	0.004	0.005
			(0.195)	(0.194)	(0.079)	(0.080)
	0	1	0.001	-0.005	-0.066	-0.075
			(0.130)	(0.131)	(0.061)	(0.061)
	1	0	0.126	0.118	-0.010	-0.009

			(0.116)	(0.116)	(0.053)	(0.053)
	1	1	-0.026	-0.023	-0.119	-0.113
			(0.214)	(0.214)	(0.093)	(0.093)
$\boldsymbol{log(D_{iq}^{IND+}+1)}$	0	0	0.055	0.058	0.088	0.088
			(0.186)	(0.186)	(0.078)	(0.079)
	0	1	-0.001	0.009	-0.091	-0.096*
			(0.151)	(0.151)	(0.058)	(0.057)
	1	0	-0.019	-0.006	-0.062	-0.061
			(0.122)	(0.122)	(0.057)	(0.059)
	1	1	-0.056	-0.044	-0.298**	-0.297**
			(0.163)	(0.163)	(0.115)	(0.120)
D(-1)	0	0	0.233	0.232	-0.008	-0.001
			(0.185)	(0.185)	(0.068)	(0.064)
	0	1	0.230	0.225	-0.009	-0.013
			(0.154)	(0.154)	(0.043)	(0.043)
	1	0	0.040	0.036	0.067	0.067
			(0.111)	(0.112)	(0.046)	(0.047)
	1	1	-0.002	0.013	-0.157*	-0.153*
			(0.174)	(0.174)	(0.085)	(0.084)
D(-2)	0	0	-0.173	-0.174	-0.134	-0.133
			(0.195)	(0.195)	(0.107)	(0.107)
	0	1	-0.025	-0.023	0.053	0.061
			(0.126)	(0.124)	(0.048)	(0.047)
	1	0	0.019	0.023	-0.040	-0.038
			(0.078)	(0.078)	(0.063)	(0.062)
	1	1	-0.027	-0.051	0.213***	0.212***
			(0.184)	(0.184)	(0.070)	(0.070)
D(-3)	0	0	0.159	0.147	0.086	0.080
			(0.255)	(0.255)	(0.102)	(0.103)
	0	1	0.128	0.133	-0.061	-0.048
			(0.146)	(0.145)	(0.056)	(0.051)
	1	0	-0.151*	-0.148*	-0.009	0.001
			(0.084)	(0.085)	(0.060)	(0.061)
	1	1	-0.181	-0.150	-0.012	-0.006
			(0.185)	(0.187)	(0.076)	(0.073)
D(+1)	0	0	-0.050	-0.052	-0.029	-0.028
			(0.195)	(0.195)	(0.066)	(0.064)
	0	1	-0.237	-0.217	-0.075	-0.069
			(0.159)	(0.159)	(0.053)	(0.053)
	1	0	-0.110	-0.102	0.039	0.035
			(0.125)	(0.125)	(0.049)	(0.048)
	1	1	-0.080	-0.055	-0.145	-0.138
			(0.245)	(0.246)	(0.110)	(0.103)
D(+2)	0	0	0.068	0.053	-0.012	-0.010
			(0.249)	(0.248)	(0.084)	(0.085)
	0	1	-0.043	-0.058	0.008	-0.005
			(0.167)	(0.167)	(0.051)	(0.052)
	1	0	-0.034	-0.043	-0.059	-0.066
			(0.090)	(0.091)	(0.058)	(0.058)
	1	1	0.178	0.171	-0.027	-0.037
			(0.185)	(0.185)	(0.098)	(0.102)

Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
VC Fund FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Quarter × Industry FE	No	Yes	No	Yes
Constant	0.392**	0.258*	0.867***	0.712***
	(0.184)	(0.153)	(0.082)	(0.113)
Observations	22,907	22,907	23,081	23,081
R-squared	0.042	0.044	0.018	0.021
Number of FundID	2,774	2,774	2,782	2,782

Table T.17 Haussman Test

b = consistent under Ho and Ha; obtained from xtreg		
B = inconsistent under Ha, efficient under Ho; obtained from xtreg		
Test:	Ho:	difference in coefficients not systematic
	chi2(112) = (b-B)'[(V_b-V_B)^(-1)](b-B) = 180.43 Prob>chi2 = 0.0000	

Table T.18 Dynamic Effects of Treatment Intensity × Round Number at the Fund-Level

VARIABLE	*Syndicate*	*Leadinvestor*	*Round*	B
$log(D_{iq}^{IND-}+1)$	1	1	1	-0.292
	1	1	2	-1.157***
	1	1	3	-0.246
	1	1	4	0.088
	1	1	5	-0.740
	1	1	6	-0.075
	1	1	7	0.794
	1	1	8	-1.233
	1	1	9	0.001
	1	1	10	-0.355
	1	1	11	2.022*
	1	1	12	-3.370***
	1	1	14	-4.803**
D(-1)	1	1	1	0.015
	1	1	2	-0.268
	1	1	3	-0.013
	1	1	4	-0.482
	1	1	5	-0.521*
	1	1	6	-0.665*
	1	1	7	-0.724
	1	1	8	-0.945
	1	1	9	-0.039
	1	1	10	-0.353**
D(-2)	1	1	-	0.081
D(-3)	1	1	-	0.028
D(+1)	1	1	-	-0.000
D(+2)	1	1	-	-0.028
$log(D_{iq}^{IND+}+1)$	1	1	-	-0.023
D(-1)	1	1	-	0.028
D(-2)	1	1	-	-0.101
D(-3)	1	1	-	-0.144
D(+1)	1	1	-	-0.036
D(+2)	1	1	-	0.167
D × *syndicate* × *leadinvestor*				Yes
Controls				Yes
Year FE				Yes
Quarter FE				Yes
VC Fund FE				Yes
Industry FE				Yes
Quarter × Industry FE				Yes
Constant				0.275*
				(0.158)
Observations				22,907
R-squared				0.051
Number of FundID				2,774

Table T.19: Variables Definition

Variable	Definition
VC Firm/Fund Level	
Syndicate	If the average syndicate score of a given VC firm/fund is greater than the average score across all VC firms/funds in a given *q* then equal to 1, 0 otherwise. The syndicate score is the average of the *syndicate dummy* across all investment holdings of a given VC firm/fund at a given *q*.
Leadinvestor	If the average leadinvestor score of a given VC firm/fund is greater than the average score across all VC firms/funds in a given *q* then equal to 1, 0 otherwise. The leadinvestor score is the average of the *leadinvestor dummy* across all investment holdings of a given VC firm/fund at a given *q*.
Stage	If the average stage score of a given VC firm/fund is greater than the average score across all VC firms/funds in a given *q* then equal to 1, 0 otherwise. The stage score is the average of the *stage dummy* across all investment holdings of a given VC firm/fund at a given *q*.
D_{iq}^{IND-}	The investment holdings belonging to IS_q^{IND-} of a given VC firm/fund in a given *q* divided by the investment holdings VC firm/fund in a given *q*.
D_{iq}^{IND+}	The investment holdings belonging to IS_q^{IND+} of a given VC firm/fund in a given *q* divided by the investment holdings VC firm/fund in a given *q*.
IS_q^{IND-}	The GICS industry with the lowest equally-weighted return of all GICS industries in a given *q*.
IS_q^{IND+}	The GICS industry with the highest equally-weighted return of all GICS industries in a given *q*.
Investment Level	
Syndicate dummy	Equal to 1 if the syndicate size is greater than 1, otherwise 0.
Syndicate size	The number of investments into a given venture per investment round, only counting unique VC firm/funds.
Leadinvestor dummy	Equal to 1 if the investor of a given investment is leadinvestor. Leadinvestor is the investor who has invested in the first investment round and with the greatest equity stake with the condition that this stake has not been sold yet, i.e., that the investment date of a given investment is before the assigned exit date of the leadinvestor's investment.
Stage dummy	Equal to 1 if the investment is declared "later-stage", and 0 otherwise.

Figures

Figure F.1 Number of Investments Per Year

Figure F.1 depicts all investment observations per year from 1999-2021. Only the last two quarters are present in the observations from 1999 and only the first quarter of 2021 is present.

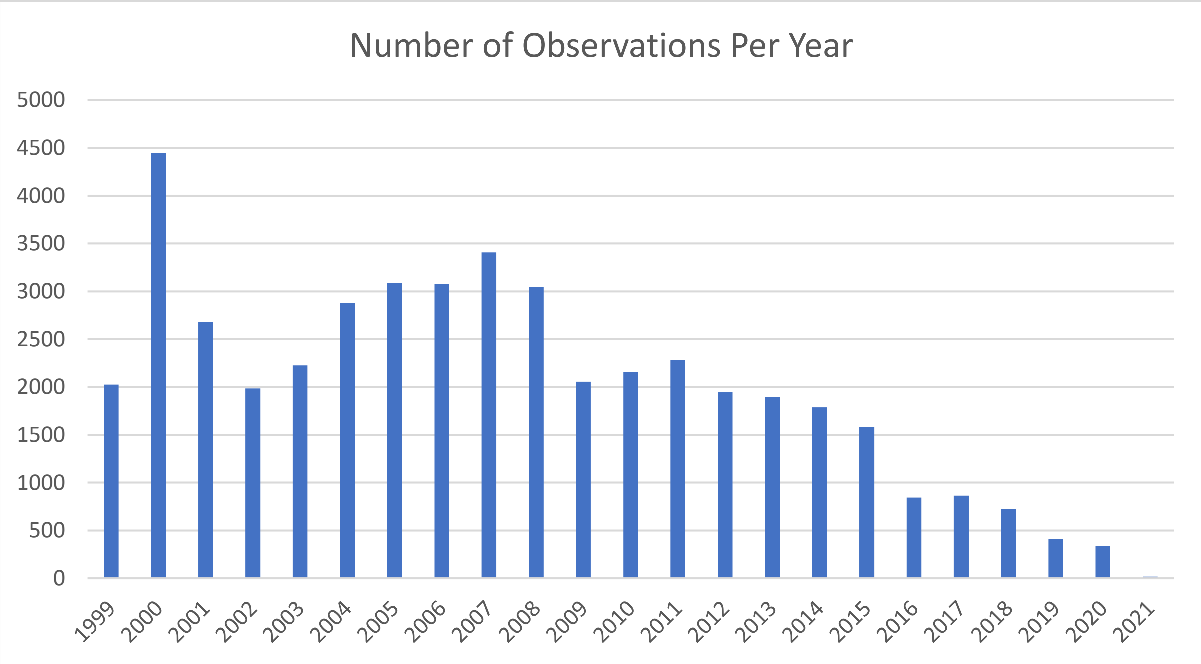


Figure F.2 Time Trend of Distracted Investments

Figure F.2 shows the total number of investments per year and the fraction of distracted investments done each year. The blue bars represent the number of investments and the orange line represents the fraction of investments that were distracted. Total number of investments is in hundreds i.e., 40=4000 etc.

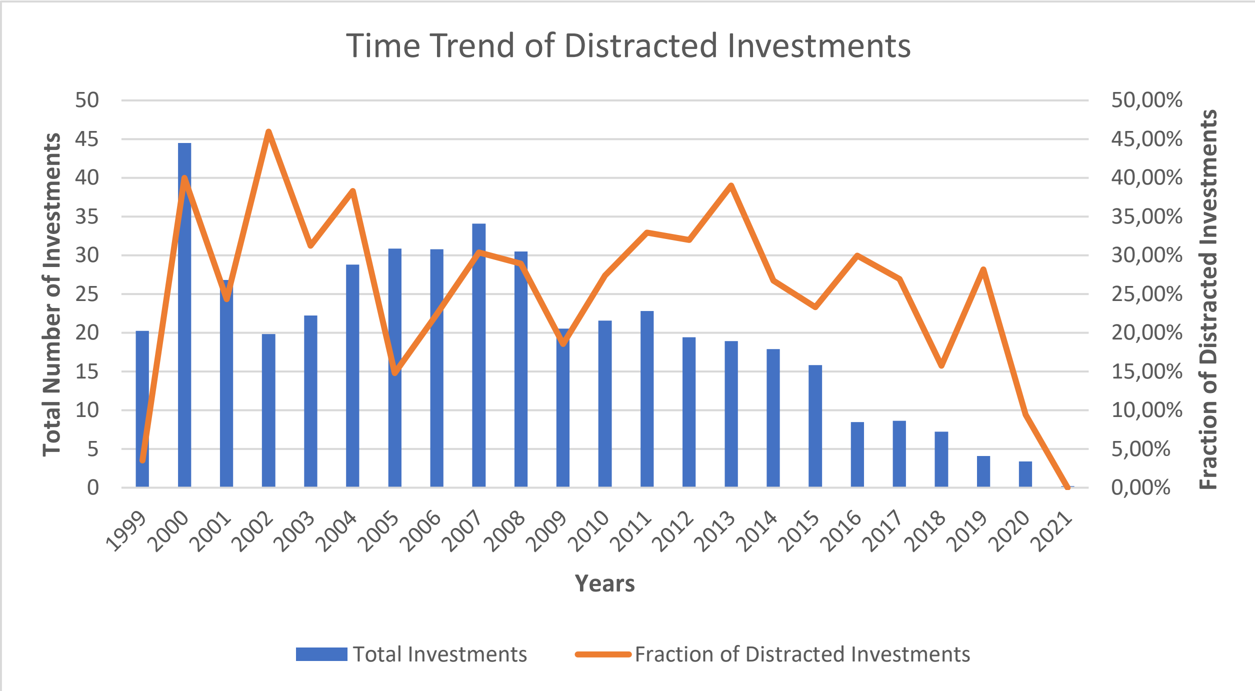
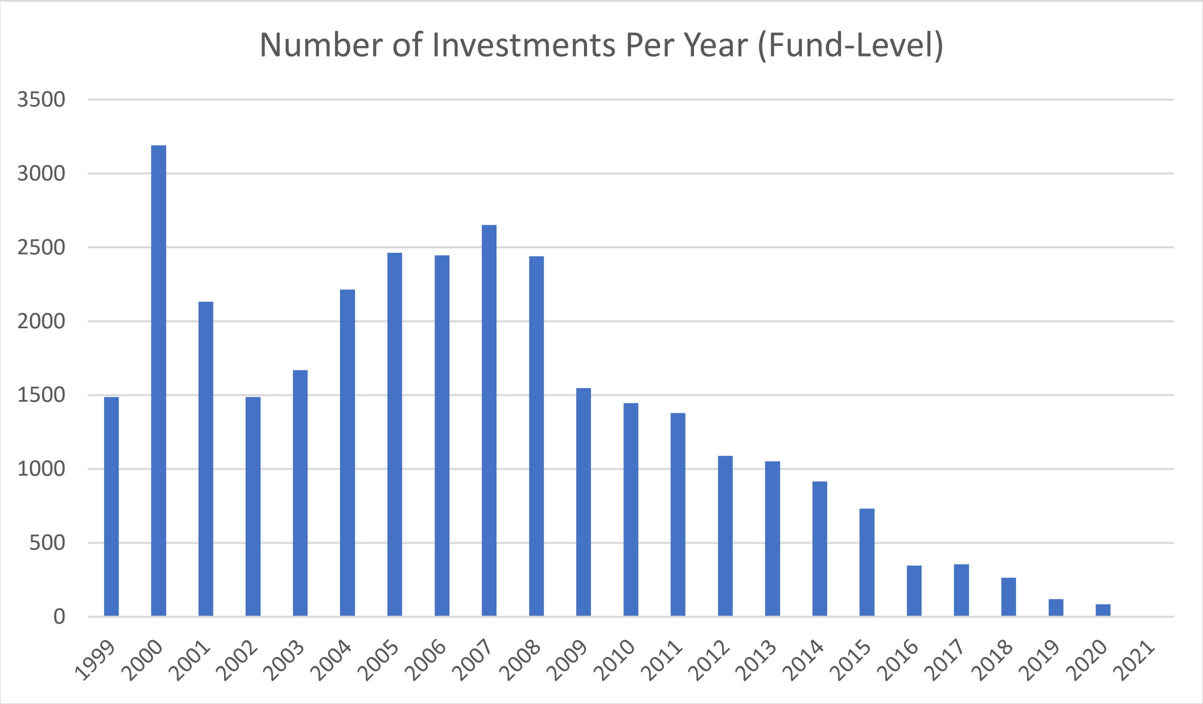


Figure F.3 Number of Investments Per Year Fund-Level

Figure F.3 depicts all investment observations per year from 1999-2021. Only the last two quarters are present in the observations from 1999 and only the first quarter of 2021 is present.



Reference List

Abuzov, R. (2020). The Impact of Venture Capital Screening. *Swiss Finance Institute,* Research Paper Series N. 19-14

Amornsiripanitch, N., Gompers, P. and Xuan, Y. (2019). More than Money: Venture Capitalists on Boards. *The Journal of Law, Economics, and Organization,* Vol. 35, Issue 3, pp. 513-543

Bennedsen, M., Pérez-Gonzalez, F. and Wolfenzon, D. (2010). Do CEOs Matter? Evidence from Hospitalization Events. *Journal of Finance,* Vol. 75, Issue 4, pp. 1877-1911

Bernstein, S., Giroud, X. and Townsend, R. (2016). The Impact of Venture Capital Monitoring. *The Journal of Finance,* Vol. 71, Issue 4, pp. 1591-1622

Boocock, G. and Woods, M. (1997). The Evaluation Criteria used by Venture Capitalists: Evidence from a UK Venture Fund. *International Small Business Journal,* Vol. 16, Issue 1, pp. 36-57

Bryman, A. and Bell, E. (2015). *Business Research Methods.* 4th Edition. Oxford University Press. New York, United States of America.

Chemmanur, T., Krishnan, K. and Nandy, D. (2011). How Does Venture Capital Financing Improve Efficiency in Private Firms? A Look Beneath the Surface. *The Review of Financial Studies,* Vol. 24, Issue 12, pp. 4037-4090

Croce, A., Marti, J. and Murtinu, S. (2013). The impact of venture capital on the productivity growth of European entrepreneurial firms: 'Screening' or 'value added' effect? *Journal of Business Venturing,* Vol. 28, Issue 4, pp. 489-510

Cumming, D., Fleming, G. and Schweinbacher, A. (2005). Liquidity Risk and Venture Capital Finance. *Financial Management,* Vol. 34, Issue 4, pp. 77-105

Cumming, D. (2006). The Determinants of Venture Capital Portfolio Size: Empirical Evidence. *Journal of Business* Vol. 79, Issue 3, pp. 1083–1126

Dessi, R. and Yin, N. (2012). The impact of Venture Capital on Innovation. *The Oxford Handbook of Venture Capital.* Oxford University Press, Inc. New York.

Fodor, A., Jorgensen, R. and Stowe, J. (2021). Financial clusters, industry groups and stock return correlations. *Journal of Financial Research,* Vol. 44, Issue 1, pp. 121-144

Fried, V. and Hisrich, R. (1994). Toward a Model of Venture Capital Investment Decision Making. *Financial Management,* Vol. 23, Issue 3, pp. 28-37

Gompers, P. (1996). Grandstanding in the venture capital industry. *Journal of Financial Economics,* Vol. 42, Issue 1, pp. 133-156

Gompers, P., Gornall, W., Kaplan, S. and Strebulaev, I. (2020). How do venture capitalists make decisions? *Journal of Financial Economics,* Vol. 135, Issue 1, pp. 169-190

Gompers, P. & Lerner, J. (1996). The Use of Covenants: An Empirical Analysis of Venture Partnership Agreements. *Journal of Law and Economics*, Vol. 39, Issue 2, pp. 463-498

Gorman, M. and Sahlman, W. (1989). What do venture capitalists do? *Journal of Business Venturing*, Vol. 4, Issue 4, pp. 231-248

Gornall, W. and Strebulaev, I. (2015). The Economic Impact of Venture Capital: Evidence from Public Companies. *SSRN Electronic Journal*, working paper

Griliches, Z. and Mairesse, J. (1995). Production Functions: The Search for Identification. *NBER Working Papers 5067*, National Bureau of Economic Research, Inc.

Hair, J., Page, M. and Brunsvel, N. (2020). *Essentials of Business Research Methods.* 4th Edition. Routledge. New York, United States of America. E-Book.

Hallet, R. (2017). These are the industries attracting the most venture capital. *World Economic Forum.* Available Online: https://www.weforum.org/agenda/2017/02/these-are-the-industries-attracting-the-most-venture-capital/#:~:text=Industry%20investment&text=Software%20investment%20accounts%20for%2036.2,and%20equipment%20and%20industrial%20energy. [Accessed: 15 May 2021]

Hellmann, T. and Puri, M. (2000). The Interaction between Product Market and Financing Strategy: The Role of Venture Capital. *Review of Financial Studies,* Vol. 13, Issue 4, pp. 959-984

Hellmann, T. and Puri, M. (2002). Venture Capital and the Professionalization of Start-Up Firms: Empirical Evidence. *The Journal of Finance,* Vol. 57, Issue 1, pp. 169-197

Hsu, D. (2004). What Do Entrepreneurs Pay for Venture Capital Affiliation? *The Journal of Finance,* Vol. 59, Issue 4, pp. 1805-1844

Hyder, S. (2021). The Changing Landscape of Venture Capital in 2021: From DeFi to Raising a Round. *Forbes Magazine.* Available Online: https://www.forbes.com/sites/shamahyder/2021/04/01/the-changing-landscape-of-venture-capital-in-2021-from-defi-to-raising-a-round/?sh=411ecaea1444 [Accessed: 29 April 2021]

Jääskeläinen, M., Maula, M. and Seppä, T. (2006). Allocation of Attention to Portfolio Companies and the Performance of Venture Capital Firms. *Entrepreneurship Theory and Practice,* Vol. 30, Issue 2, pp. 185-206

Kacperczyk, M., Nieuwerburgh, S. and Veldkamp, L. (2016). A Rational Theory of Mutual Funds' Attention Allocation. *Econometrica,* Vol. 84, Issue 2, pp. 571-626

Kaplan, S. and Lerner, J. (2010). It Ain't Broke: The Past, Present, and Future of Venture Capital. *Journal of Applied Corporate Finance,* Vol. 22, Issue 2, pp. 36-47

Kaplan, S. and Schoar, A. (2005). Private Equity Performance: Returns, Persistence, and Capital Flows. *The Journal of Finance,* Vol. 60, Issue 4, pp. 1791-1823

Kaplan, S., Sensoy, B. and Strömberg, 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,* Vol. 64, Issue 1, pp. 75-115

Kaplan, S. and Strömberg, P. (2000). How Do Venture Capitalists Choose Investments? Working Paper, University of Chicago, Vol. 21, pp. 55-93

Kaplan, S. and Strömberg, P. (2001). Venture Capital As Principals: Contracting, Screening snd Monitoring. *American Economic Review,* Vol. 91, Issue 2, pp. 426-430

Kempf, E., Manconi, A. and Spalt, O. (2017). Distracted Shareholders and Corporate Actions. *The Review of Financial Studies,* Vol. 30, Issue 5, pp. 1660-1695

Lerner, J. (1994). Venture capitalists and the decision to go public. *Journal of Financial Economics,* Vol. 35, Issue 3, pp. 293-316

Lerner, J. (1995). Venture Capitalists and the Oversight of Private Firms. *The Journal of Finance,* Vol. 50, Issue 1, pp. 301-318

Macmillan, I., Kulow, D. and Khoylian, R. (1989). Venture capitalists' involvement in their investments: Extent and performance. *Journal of Business Venturing,* Vol. 4, Issue 1, pp. 27-47

Metrick, A. and Yasuda, A. 2010, *Venture Capital & the Finance of Innovation.* 2nd Edition. John Wiley & Sons, Inc. Hoboken, United States of America. E-Book.

Puri, M. and Zarutskie, R. (2012). On the Life Cycle Dynamics of Venture-Capital- and Non-Venture-Capital-Financed Firms. *The Journal of Finance,* Vol. 67, Issue 6, pp. 2247-2293

Puskoor, P. (2020). Venture Capital Funds Need to Innovate and Differentiate. Here's How They Can. *Forbes Magazine.* Available online:

https://www.forbes.com/sites/forbesfinancecouncil/2020/11/18/venture-capital-funds-need-to-innovate-and-differentiate-heres-how-they-can/?sh=4664d1e4320c [Accessed: 29 April 2021]

Rajan, T. (2010). Venture Capital and Efficiency of Portfolio Companies. *IMB Management Review,* Vol. 22, Issue 4, pp. 186-197

Rin, M., Hellmann, T. and Puri, M. (2013). A Survey of Venture Capital Research. *Handbook of the Economics of Finance,* Vol 2, pp. 573-648

Roberts, M. and Whited, T. (2013). Endogeneity in Empirical Corporate Finance. *Handbook of the Economics of Finance*, Vol. 2, pp. 493-572

Sahlman, W. (1990). The structure and governance of venture-capital organizations. *Journal of Financial Economics,* Vol. 27, Issue 2, pp. 473-521

Steier, L. and Greenwood, R. (1995). Venture Capitalist Relationships in the Deal Structure and Post-Investment Stages of New Firm Creation. *Journal of Management Studies*, Vol. 32, Issue 3, pp. 337-357

Stein, L. and Zhao, H. (2016). Distracted Directors. Working Paper, Arizona State University.

Sørensen, M. (2006). How Smart is Smart Money? A Two-Sided Matching Model of Venture Capital. *The Journal of Finance*, vol 62, Issue 6, pp. 2725-2762

Tian, X. (2012) The Role of Venture Capital Syndication in Value Creation for Entrepreneurial Firms. *Review of Finance,* Vol. 16, Issue 1, pp. 245-283

Wright, M. and Lockett, A. (2003). The Structure and Management of Alliances: Syndication in the Venture Capital Industry. *Journal of Management Studies*, Vol. 40, Issue 8, pp. 2073-2102

Yung, C. (2009). The Long-Run Supply and Demand for Venture Capital Funds: Information and Endogenous Entry. *SSRN Electronic Journal*, working paper

Yung, C. (2012). Venture Capital Before The First Dollar: Deal Origination, Screening, and Evaluation. *The Oxford Handbook of Venture Capital.* Oxford University Press, Inc. New York.

Appendix

Appendix 1: T-Test for Differences in Mean Between Missing and Non-Missing Data

Round Number

Group	Obs	Mean	Std.Err	Std. Dev.	[95% Conf. Interval]	
0	35,847	3.039473	.014132	2.67566	3.011774	3.067173
1	92,786	3.475212	.0094681	2.88406	3.456654	3.493769
Combined	128,633	3.353782	.0079025	2.834259	3.338293	3.36927
diff = mean(0) - mean(1)						
Ho: diff = 0		Ha: diff < 0	Ha: diff != 0	Ha: diff > 0		t = -25.6158
		Pr(T < t) = 0.0000	Pr(|T| > |t|) = 0.0000	Pr(T > t) = 1.0000		

Equity Invested

Group	Obs	Mean	Std.Err	Std. Dev.	[95% Conf. Interval]	
0	35,847	1.01e+07	139970	2.65e+07	9848168	1.04e+07
1	92,786	1.92e+07	177095.2	5.39e+07	1.88e+07	1.95e+07
Combined	128,633	1.66e+07	134043.3	4.81e+07	1.64e+07	1.69e+07
diff = mean(0) - mean(1)						
Ho: diff = 0		Ha: diff < 0	Ha: diff != 0	Ha: diff > 0		
		Pr(T < t) = 0.0000	Pr(|T| > |t|) = 0.0000	Pr(T > t) = 1.0000		t = -40.0837

Fund Equity Invested

Group	Obs	Mean	Std.Err	Std. Dev.	[95% Conf. Interval]	
0	35,847	2447134	29082.36	5506252	2390132	2504136
1	92,786	3842163	34968.77	1.07e+07	3773624	3910701
Combined	128,633	3453401	26551.12	9522675	3401361	3505441
diff = mean(0) - mean(1)						
Ho: diff = 0		Ha: diff < 0	Ha: diff != 0	Ha: diff > 0		
		Pr(T < t) = 0.0000	Pr(|T| > |t|) = 0.0000	Pr(T > t) = 1.0000		t = -30.6722