The Effect of SoftBank Vision Fund on Venture Capital Cycles

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Abstract

The venture capital (VC) industry is highly volatile and undergoes cycles of boom and bust. This research explores the influence of the SoftBank Vision Fund (SBVF), a 100 billion USD venture capital fund raised by the Japanese multinational conglomerate telecommunications company SoftBank, as a disruptor in the venture capital industry and as a major driver of directions of current and future swings in venture capital cycles in terms of fund behavior and investment. I provide evidence on the effect of the entrance of the Vision Fund on changes in two things: (1) fund size and (2) investment focus of funds raised by VC firms. I work with a data sample of 1123 venture capital funds in the United States with initial closing years of 2011 to 2019, from VentureXpert, one of two major databases used by researchers. I use an empirical difference-in-differences design to look at both extensive and intensive margin effects on the two outcomes of interest in this paper. Though my results are not all significant, they provide important insight and confirm potential factors that attract or deter VC firms from following SBVF in its strategy of raising huge funds and investing in technology and other industries in which SBVF is interested. The factors that attract VC firms to follow SBVF in its strategy include behavioral factors, beliefs formed by reputation signaling or certification, and herding. The factors that deter VC firms from following SBVF in its strategy include agency costs, long-term reputation consequences, operational costs, status quo bias, and situation awareness. This paper thus takes steps toward learning about the extent of and channels through which shocks like SBVF may influence and disrupt the U.S. VC industry. The findings here have major implications in terms of real challenges and vulnerabilities that may arise from the end of a cycle driven by influences like SBVF, as well as for the change in innovation levels and consequently rate of economic growth in the United States.

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I. INTRODUCTION

The venture capital (VC) industry is highly volatile and undergoes cycles of boom and bust. Much literature covers the factors that influence market cycles in private equity and venture capital. Studies in the past have explored a few broad areas in which cycles occur: fundraising (Gompers and Lerner, 1998), the amount of investments made (Gompers, Kovner, Lerner, and Scharfstein, 2008), and the valuation or performance of these investments (Gompers and Lerner, 2000). Factors that drive these cycles in VC are many and can be macroeconomic, regulatory, and performance-related. These factors may include public market signals, changes in capital gains tax rates, easing of institutional investment restrictions, research and development expenditures, and reputation and past performance of the VC firms themselves.

One driver of these cycles includes fund inflows. This factor is interesting especially because the levels and patterns of fund inflows themselves have been changing, as evidenced by the recent rise of mega funds, funds typically defined as bigger than 1 billion dollars in size. Much literature discusses the effect of these inflows on the VC industry. For instance, inflows of capital into venture funds have been found to increase the valuation of these funds' investments (Gompers and Lerner, 2000). Evidence that seems to support this finding can be observed in the statistics of recent years. Figure A in the Appendix, which shows private equity fundraising in the last decade from 2009-2019, shows that in the United States, VC fund inflow levels or levels of aggregate capital raised has increased up to and held steady at a peak in the recent years of 2017 to 2019. Figure B in the Appendix, which is a line graph of the number of companies that reach unicorn status each year in the 2014-2018 time range, shows a steady increase in the number of unicorns in 2016-2018. The figure shows a value of 151 newly minted unicorns in the year 2018, though a lot of these companies may potentially be overvalued.

This paper further builds upon the literature on the effects of fund inflows on venture capital cycles. This research idea explores the influence of the SoftBank Vision Fund (SBVF), a 100 billion USD venture capital fund raised by the Japanese multinational conglomerate telecommunications company SoftBank, as a disruptor in the venture capital industry and as a major driver of directions of current and future swings in venture capital fund behavior and investment. I provide evidence on the effect of the entrance of the Vision Fund on changes in two things: (1) fund size and (2) investment focus of funds raised by VC firms. In other words, for looking at investment industry focus shift, the question I would like to answer is: after the venture capital industry became aware of the large presence and size of SoftBank's Vision Fund, will new funds raised by venture capital firms begin to shift their industry focus away from or toward technology and other industries in which SoftBank Vision Fund heavily invests? For looking at fund size changes, the question to answer is: will these funds also begin to deviate from the size trends of the pre-Vision Fund period?

The sample consists of 1123 venture capital funds in the United States with initial closing years of 2011 to 2019. The data is from VentureXpert, which is one of two major databases used by researchers and is downloaded through SDC Platinum. The empirical strategy is to use difference-in-differences design to look at both extensive and intensive margin effects on the two outcomes of interest in this paper. Intensive margin effects study whether incumbent or "already-established" VC firms make changes in their subsequent funds in the two dependent variables of interest in this paper (fund size and industry focus) after the cutoff marked by a SoftBank Vision Fund announcement. Extensive margin effects study changes in our dependent variables in the U.S. VC industry through looking at first-time funds raised before and after the SBVF announcement by “newly-established” VC firms. Cross-sectional variation in funds’ industries of focus allows me to document findings using the difference-in-differences framework.

My analysis on the existence and direction of industry focus shifts and fund size changes will depend on which of three size categories I place a fundraising VC firm. Analysis will be done on each size category separately and the size categories are “lower market,” “middle market,” and “mega,” to represent the smallest, middle, and largest sized funds in the United States venture capital industry from 2011 to 2019.

The following summarizes results from analysis. I call VC funds that have an industry focus in SoftBank Vision Fund’s industries of focus, or broadly technology, “SBVF industry” or “SoftBank industry” funds:

- For already-established firms and the dependent variable of fund size, results show varying results across all three size categories. Low size funds see positive size change and mega size funds see negative size change. Middle size funds see initial positive size change but then negative change later on. The results here, though, are not significant at the confidence level of 90%.
- For newly-established firms and the dependent variable of fund size, results show that first-time funds became increasingly large after SBVF entry. The results here, again, are not significant at the confidence level of 90% though.
- For already-established firms and the dependent variable of industry shift, results show that low and mega size funds shift away from investment in SBVF industries, while middle size funds shift toward investment in SBVF industries. The shift away from SBVF industries exhibited by low and mega size funds is more significant than the shift toward SBVF industries exhibited by middle size funds. Results here are at least significant at the confidence level of 90%.
- For newly-established firms and the dependent variable of industry shift, results show that first-time funds increasingly invested in primarily non-SBVF industries after SBVF entry. The results here, though, are not significant at the confidence level of 90%.

My results confirm potential factors that attract or deter VC firms from following SBVF in its strategy of raising huge funds and investing in technology and other industries in which SBVF is interested. Factors that attract VC firms to follow SBVF in its strategy include behavioral factors, beliefs formed by reputation signaling or certification, and herding. Factors that deter VC firms from following SBVF in its strategy include agency costs, long-term reputation consequences, operational costs, and status quo bias. Another significant factor that may vary with fund size is situation awareness, which also can offset behavioral responses toward mimicking SBVF's strategy. The interpretation of my results depends on my claim that in the environment of interest in this paper, entrepreneurs will weight money over non-monetary support in deciding which VC firms' support to accept.

The outcome of interest here of industry focus shift in VC firms, in particular, relates to a broader concern of changes in innovation in the United States, which is driven largely by scientific and technological ideas and knowledge. Changes in innovation can then affect the rate of economic growth. A recent paper on innovation (Bloom, Jones, Reenen, and Webb, 2020) claims that ideas and the growth they imply may be getting harder to find, even as research effort rises, research productivity is declining. Another paper studying innovation (Arora, Belenzon, and Patacconi, 2015) also finds that scientific capabilities and value attributable to scientific research has decreased. Relating back to the VC industry and the question of interest in this paper, the research in Bloom, Jones, Reenen, and Webb (2020) implies the possibility that VC firms may shift away from investing in technological and scientific industries because the supply of innovative or value-adding ideas in startups is running low. On the other hand, the research in Arora, Belenzon, and Patacconi (2015) implies another possibility that VC firms may perhaps themselves contribute to this big picture trend of declining of innovation if they shift away from investing in technology and science-related industries for their own reasons. This industry focus shift away from science and technology would lead to less funding for potential innovative and value-adding startups.

Venture capital cycles are important to study for many reasons; one reason is due to potential issues that may arise upon the cycles' end. If indeed in the exploration of this research question, I find that these groups of players in the VC landscape are tied to or affected by SBVF's actions, then in the unfortunate scenario where SBVF fails such as through losing investors, influence, or credibility, these VC groups could be highly vulnerable as they are quickly exposed to a new environment.

This potential issue could spell challenges for the VC industry going forward. SoftBank's behavior and influence affects investors, startups, the broader U.S. economy, such as through stock markets and entire governments. More generally, studying mega funds and their role in the VC market is significant to all players who are in or interact with the VC industry. The VC industry in turn significantly impacts startup success, shown by Puri and Zarutski (2009); innovation, shown by Kortum and Lerner (2000), Kortum and Lerner (2001), Hellmann and Puri (2000), and Sørensen (2007); economic growth, shown by Bernstein, Lerner, Sorensen, and Stromberg (2017); and job creation as shown by Gompers and Lerner (2001).

This paper is again related to literature on factors that influence venture capitalists in their decisions on various aspects of the funds they raise, such as in fundraising (Gompers and Lerner, 1998), the amount of investments made (Gompers, Kovner, Lerner, and Scharfstein, 2008), and the valuation or performance of these investments (Gompers and Lerner, 2000). The paper also contributes to work on behavioral responses venture capitalists have to shocks to the industry and on the role of certification, herding, and agency costs in decision-making in the finance industry.

No large scale, comprehensive research project has been done on mega funds in VC yet. If significant results are found, this project could become a core paper and foundation for future research in this area.

The rest of the paper is organized as follows. Section II provides descriptive background and evidence for hypothesis formation. Section III discusses data and empirical strategy. Section IV states results. Section V discusses analysis and interpretation of results. Section VI concludes and offers avenues for future research.

II. BACKGROUND AND HYPOTHESES

Venture capital is a form of private equity. Investment in private equity is usually done through a general partner-limited partner structure, where general partners, or GPs, are usually private equity firms. Limited partners, or LPs, are investors that provide capital to the GP, and they are usually large institutional investors and/or wealthy individuals. The total amount of capital committed to the fund is what venture capital and private equity databases often record as fund size. The GP then usually takes a total of around 10 years to invest capital in their investments, which are called portfolio companies, seek exits for these portfolio companies, and return capital from these exits to LPs. The GP may then seek to raise separate next funds when it has already put to work most of its current fund's raised capital.

Many startups seek venture capital as a significant source of outside financing as opposed to other options. Startups, or entrepreneurial firms, often have trouble receiving funding through other options like bank loans and other debt financing due to asymmetric information and huge uncertainty from intangible assets and potential years of negative earnings. The design of the venture capital structure allows the possibility for high risk, but potentially also high reward, private firms to receive funding. Venture capitalists, in addition to monetary support, also actively monitor their investments and provide nonmonetary support such as governance, operational guidance, and networks. Examples of well-known companies that have received venture capital financing include Apple Computer, Intel, Microsoft, Federal Express, Staples, and Starbucks.

The question investigated in this paper is particularly interesting as the venture capital industry has seen a rise in mega funds in the recent years of 2017 and 2018, where a mega fund in venture capital is typically considered a fund of 1 billion or larger, as well as continued high investment in technology companies. Many U.S. venture capital firms, if they have the capability, have increasingly been raising mega funds, such as those of Sequoia, Andreessen Horowitz, and Bessemer Venture Partners. Figure C in the Appendix, which presents the distribution of U.S. VC fund sizes from 2008-2018, shows that the percentage of U.S. venture capital funds in size categories of 0-25, 25-100, 100-250, 250-500, and >500 million USD have stayed constant in the past few years, especially from 2012-2018, but that the total AUM of funds in the >500 million USD category has steadily increased over time. This implies that of the VC funds larger than 500 million USD in size, each are growing bigger to account for more and more of the percentage of total AUM in the U.S. venture capital industry each year. Figure D in the Appendix presents the percentage of U.S. VC investment deals made in certain industries in 2014-2019, showing a majority in the "Information Technology" industry category, with "Healthcare" and "Consumer Discretionary" following close behind.

Understanding why SoftBank Vision Fund is a potential disruptor to the VC industry requires understanding the Vision Fund itself. The Vision Fund's intentions are to invest long-term in companies that contribute to the next "age of innovation," as SoftBank stated in a May

22nd 2017 press release. The Vision Fund has invested funds from its 100 billion USD money supply into some of the biggest technology startups in the landscape today, including Uber, DoorDash, Slack, and most recently notoriously, WeWork. An interesting fact about the Vision Fund is that up to 45 billion of the 100 billion dollars raised for the Vision Fund is funded by the Saudi Arabia government's Public Investment Fund. ("The Investor") On October 14th, 2016, SoftBank announced the Vision Fund's presence and target size of 100 billion USD in its first known official disclosure in a press release on its website, and on May 22nd, 2017, SoftBank officially announced its first major close of over 93 billion USD in another press release.

Masayoshi Son, the CEO of SoftBank, has a broad investment strategy and definition of "technology." The strategy announced in SoftBank's 2017 disclosure is broad; it seeks to "acquire minority and majority interests in both public and private companies, from emerging technology businesses to established, multi-billion dollar companies requiring substantial growth funding." Within the technology sector, the Fund said it would target many different sub-sectors, such as "Internet of Things, artificial intelligence, robotics, mobile applications and computing, communications infrastructure and telecoms, computational biology and other data-driven models, cloud technologies and software, consumer internet businesses and financial technology." SoftBank CEO Masayoshi Son aims to not only invest in technology companies with the potential to become unicorns but also boost to entire sectors ("Masayoshi"). Table A gives the list of portfolio companies SoftBank Vision Fund holds, categorized by sector.

Again, this paper's analysis focuses on the existence and extent of disruptive effects of SoftBank and its Vision Fund on the VC industry.

SECTION II.A: HYPOTHESIS FORMATION

The standard methodology in economic theory is to portray firms as profit maximizing entities. Following this standard, we will assume that venture capital firms seek to maximize their value and profitability, or their returns net of costs from the funds they raise and operate.

My analysis also assumes that the behavior of the SoftBank Vision Fund (SBVF) is not affected by the behavior of players in the rest of the venture capital industry given its sheer size and power. Another relevant thing to understand for this paper's question, as Poterba (1989) argues, is that many fundraising changes in the VC industry can be due to changes in supply or demand for venture capital.

In discussing and forming hypotheses for the question of interest in this paper, I will use the following structure. I consider intensive and extensive margin effects separately. Intensive margin effects study whether incumbent VC firms make changes in their subsequent funds in the two dependent variables of interest in this paper (fund size and industry focus) after the cutoff marked by a SoftBank Vision Fund (SBVF) announcement. Extensive margin effects study changes in our dependent variables in the U.S. VC industry through looking at first-time funds raised before and after the SBVF announcement. Then, within each of intensive and extensive margin analysis, I form hypotheses about the behavior of low, middle, and mega sized VC firms in regard to (1) fund size and (2) industry focus. And in doing so, I discuss both supply and demand perspectives for VC services. VC firms here represent the supply side, and VC firm clients, who are entrepreneurs with their startups, represent the demand side for VC services.

Again, the reasoning and framework behind the discussion and motivation of my hypotheses is the following. On the supply side, or the perspective of VC firms, the entrance of SBVF may lead VC firms to consider making significant changes in fund size or industry focus due to a combination of behavioral factors, beliefs formed by reputation signaling or certification, and herding. However, when these potential actions are motivated more by behavioral rather than rational factors, VC firms may take on agency costs additional to agency costs that are already known to exist in the common and accepted GP-LP structure of the VC industry. I consider how VC firms will weigh the combination of the agency costs incurred as a result of SBVF's entrance, long-term reputation consequences, operational costs, and status quo bias, in their decisions to implement or refrain from changes in fund size and industry focus. My hypotheses also take into account the demand side, or the perspective of the clients of VC firms, which are entrepreneurial firms.

II.A.i Intensive Margin

An assumption I make in the intensive margin analysis is that SBVF should only affect VC firms that also invest in SB industries. I am assuming no spillover effects to VC firms that do not invest in SB industries.

II.A.i.a Supply Side Perspective

II.A.i.a.i Forces Pushing for Following the Strategy of SBVF

Let us begin by discussing the relationship between venture capital firms and entrepreneurs' startups. Historically, startups pitched to VC firms for funding. However, in recent years, money has increasingly been flowing the opposite way – VC firms often find themselves throwing money at startups. This phenomenon has been happening at the level of both early stage startups, such as due to the "spray and pray" trend (Ewens, Nanda, Rhodes-Kropf, 2018), and later stage startups, such as due to the deregulation of the private equity industry with securities laws like the National Securities Markets Improvement Act (NSMIA) (Ewens and Farre-Mensa, 2019).

In the midst of this recent environment of throwing money at startups enters the SBVF, which executes the same strategy but at a much larger scale and with a lot more glamour. SBVF aimed to excite onlookers as it painted a glamorous image for itself as the leader of the technology future and transforming the world.

For instance, in SB's first press release about the Vision Fund, posted on October 14, 2016, Masayoshi Son, Chairman & CEO of SoftBank Group Corp., quoted as saying:

> "With the establishment of the SoftBank Vision Fund, we will be able to step up investments in technology companies globally. Over the next decade, the SoftBank Vision Fund will be the biggest investor in the technology sector. We will further accelerate the Information Revolution by contributing to its development."

In addition, SB's second press release about the Vision Fund, posted on May 22, 2017, said under the "Investment Strategy" section that "The Fund will target meaningful, long-term investments in companies and foundational platform businesses that seek to enable the next age of innovation."

SB also emphasized the positive social impact of the world transformation it envisioned. SBVF says, under the "Social Impact" page on its website:

> "We envisage a future where the world's most extraordinary companies are working together to help solve some of the biggest challenges facing humanity. The technologies we are investing in have the potential to profoundly benefit society through radical improvements in products and services, reduced costs, and improved efficiency."

With this image of grandeur and positive social impact, SBVF, again on its website under the "Work with Us" page, justifies its plan to invest huge sums of money in their companies and industries: "By removing the constraints of capital, we seek to enable founders to stave off short-term pressures and focus on building enduring companies."

Putting aside SBVF's selling to onlookers the image of being an innovative, world-transforming leader of technology and the future that would solve the biggest challenges facing humanity, it should be recognized that SoftBank Group Corporation foundationally had up to that point established itself as a credible institution through its track record as a multinational conglomerate in the telecommunications services industry and as one of the largest companies in Japan and in the world. Masayoshi Son also had developed a strong track record and reputation as the founder, CEO, and leader of SoftBank. The academic literature supports the certification effects of strong past track records in the form of greater reputation capital. In certification, an award or investment serves as a signal that conveys information about grantee quality, as Howell (2017) explained well. Douglas Cumming in his book, *Venture Capital: Investment Strategies, Structures, and Policies* speaks much about the importance of certification, signaling quality, and reputation (Cumming 2010, 319-321). In the setting of investment banks in the equity market, Chemmanur and Fulghieri (1994) note in their paper that investment banks can show greater reputation capital (and thus face less information asymmetry) through their strong past track record. The certification effect of greater reputation capital conveys information to others about a firm's quality. Here, SoftBank's strong reputation capital conveys credible high quality, and thus many investors at the time of the SBVF announcement bought into SoftBank's overall vision and its vision for its Vision Fund.

Firms, entities, and projects can also experience a positive certification effect if many other entities of strong reputational capital buy into them. Literature on information reliability, information asymmetry, moral hazard, and certification speaks to this phenomenon. Models exist of information reliability, such as the canonical ones regarding the role of financial intermediaries as information producers as in Leland and Pyle (1977) and Campbell and Kracaw (1980). Campbell and Kracaw (1980) in particular claim that financial intermediaries can reduce moral hazard problems in information production by investing enough of its own money in firms under their consideration. In an incentive model of financial intermediation by Holmstrom and Tirole (1997), uninformed lenders commit funds to firms only after an informed lender has made the commitment to monitor by investing in the project. Megginson and Weiss (1991) provides a general model of venture capital certification that emphasizes the role and importance of reputational capital in information reliability.

These papers and models imply that relatively less informed onlookers will see the strategy of more informed players as more credible if they commit money to a project. An informed player, by investing in a project, makes the commitment of monitoring the project, and it has "skin in the game." The credibility or quality of decision is further enhanced by the reputational capital of the informed player. In short, the literature implies that informed players, especially those of strong reputational capital, can have a positive certification effect on the projects, firms, or funds in which they invest money.

Turning back to the context of SBVF from the academic literature, SBVF early on announces a list of its investors, which all have relatively strong reputational capital. The largest investor is the Saudi Arabian government through its Saudi Arabia Public Investment Fund, which supplies almost half of the SBVF's money. Other investors with strong reputations that the SBVF lists on its second press release include Abu Dhabi's Mubadala Investment, Apple, Foxconn, Qualcomm, and Sharp.

Due to the above discussed certification effect of SB's and SBVF's reputation capital (as well as the SBVF selling to onlookers a visionary image), players in the VC industry may exhibit a behavioral response as VC firms that are capable of doing so seek to follow and attempt to mimic the strategy of SBVF and its promises/visions of success and returns. To explore behavioral explanations for such a response, note that according to Kahneman and Tversky (1974), people are often prone to "cognitive illusions." One of these cognitive illusions is that people may often underweight the risk of potential costs in taking certain actions. For instance, theory in psychological economics discuss the role of visceral factors and the "risk-as-feeling" perspective in decision-making. Visceral factors refer to emotions people experience while making decisions, while the "risk-as-feeling" concept describes the possibility that these visceral factors affect or even override rational assessments of risk and uncertainty in these decisions. This phenomenon has, for instance, been documented and analyzed by Bower and Wright (1992), who find that stock returns exhibit predictable patterns because people in good moods are more likely than those in bad moods to be more optimistic in estimates and judgments. In the context of this paper's question, VC firms may succumb to visceral factors in getting caught up in the glamorous appearance and visions the SBVF says it will realize. If VC firms succumb to these visceral factors as consistent with the "risk-as-feeling" perspective, then they may seek to mimic SBVF and its strategy while forgetting or underweighting the risk and potential costs of doing so.

Herding might further amplify the effect of VC firms seeking to mimic SBVF's strategy if they are capable of doing so. As Bikhchandani and Sharma (2000) describe, intuitively, an entity is said to herd if it would have made a decision without knowing other players' decisions, but it does not make that decision when it finds that others have decided not to do so. Scharfstein and Stein (1990) presented a model of reputational herding that showed that managers, such as venture capitalists, may feel compelled to follow the herd or mimic the behavior of other managers or venture capitalists if they are concerned with reputation consequences of being seen as contrarians, even it means ignoring their own information. This model has been empirically supported, such as by Chevalier and Ellison (1999) in their study of mutual fund managers and by Hong, Kubik, and Solomon (2000) in their study of equity analysts. However, a potential problem is that those who herd may do so on a decision that is costly or wrong for all of them, as Bikhchandani and Sharma (2000) point out. Many papers have provided evidence on how herding has led to amplified volatility and crises in financial markets, such as Morris and Shin (1999), Persaud (2000), and Shiller (1990). Taking a step back to look at the bigger picture, it is interesting to note that the aforementioned discussed behavioral phenomena are also some of the same that have driven the largest business cycles and bubbles of the past.

Finally, according to free cash flow theory, as explained in Jensen (1986), VCs that are getting increased cash flows, as has been occurring on an industry-wide level for the past decade as described in the "Introduction," will more likely take actions not in line with interests of LPs, such as generating agency costs by taking actions that ultimately are likely to decrease returns for LPs. In this case, these actions can include the behavioral response of falling to the influence of SBVF.

II.A.i.a.ii Forces Pushing Against Following the Strategy of SBVF

Now, the above discussion revolves around the potential for VC firms to take actions that mimic SBVF's strategy due to behavioral factors. However, there are also many counterforces to doing so. First, VC firms may take on agency costs if they follow the strategy of SBVF without also sufficiently considering rational factors. Other counterforces include ex post reputation considerations, operational costs of changing fund size and/or industry focus, as well as status quo bias.

The first counterforce I address here are potential agency costs. In a vacuum-type setting, absent outside frictions and factors such as SBVF, the venture capital industry is already evidence of consequences of agency theory and ways people have tried to minimize agency costs. Evidence includes the design of the GP-LP venture capital partnership structure, as well as the corporate governance structure of VC-backed startups where preferred rather than common shareholders often control the board and thus the firm itself (Fried and Ganor 2005).

Agency theory in general refers to difficulties that can arise when parties involved in a contract that sees exchange of risk change their actions after the contract has been made. Adam Smith in his work *The Wealth of Nations* was perhaps one of the first authors to identify the possibility of these difficulties, or agency problems, as he wrote that parties who manage an organization they do not completely own may not work for the real owners' benefit (Leepsa and Panda 2017, 77). As Fama and Jensen (1983) described, agency problems may arise because decision-makers who initiate and implement the decisions do not completely bear the effects of their choices and often do so at the expense of other parties.

Over time, much work has been done on agency theory, and many different models have surfaced, each with different assumptions about and discussed relationships among cost, performance, motivation, contractual agreements, ability, and risk averseness; these include the positivist agency (Eisenhardt, 1989), principal-agent (Harris and Raviv, 1978), and behavioral agency models (Gomez-Mejia and Wiseman, 1998).

Along with work on agency theory has come work on agency costs, or costs of agency problems (Jensen and Meckling, 1976). Jensen and Meckling (1976) described agency cost as the combination monitoring cost, bonding cost and residual loss. Monitoring cost comes from cost of monitoring and assessing performance of agents in a firm. Bonding cost has an inverse relationship with monitoring cost; it is the cost of setting up and operating according to a firm's defined system or structure. Finally, residual loss is due to inefficient managerial decisions when conflicts of interest cause managers to make decisions that are not aligned with the interests of owners (Leepsa and Panda 2017, 84-85). Agency costs are important to address, as Fama and Jensen (1983) believed they need to be controlled in order for firms to survive.

Coming back to the real environment from the vacuum-type setting, which takes back into account outside influences like the SBVF, the SBVF can lead to residual loss agency costs if VC firms do indeed succumb to behavioral motives behind following SBVF's strategy despite the existence of real costs of significant change in fund size of industry investment focus for its subsequent funds, such that following SBVF's strategy would lead to most of the related consequences and burdens to be borne by fund LPs and/or the portfolio companies themselves.

Moving on to a second interesting tension or dynamic is that though it is possible for manifestation of initial herding in making the decision to follow SBVF's strategy among VC firms concerned about reputation consequences of not doing so, according to the model in Scharfstein and Stein (1990), careful consideration of ex post reputation consequences of executing this decision may also restrain VC firms from doing so in the first place. The VC industry is highly networked and relies heavily on maintaining and enhancing reputation for continued success for the repeated need for funds (Cumming 2010, 320-321). Examples of benefits of a strong reputation include a good network of people who can provide services for portfolio companies (Sahlman, 1990), ability to have less costly and larger fundraising for future funds, better VC compensation (Gompers and Lerner, 1999), and retaining favorable access to the most profitable exit markets. If some VC firms hold longer-term perspectives and foresee that following SBVF's strategy may ex post lead to decreased returns or less success and thus believe the costs of damage to their long-term reputation are higher than the benefits of short-term reputation boosts through following the herd in mimicking SBVF's strategy, these VC firms may shy away from following SBVF's strategy from the very beginning. These VC firms that hold better foresight and longer-term visions may also tend to be more experienced, which identifies VC firm experience as a factor to control for in analysis.

The third counterforce I address here is the operational costs of changing fund size and/or industry focus. I will here first address only operational costs of changing fund size for hypothesis formation of fund size analysis, and then later address operational costs of industry shift when I form hypotheses for industry shift analysis. Generally, increasing fund size of a VC firms' subsequent fund will generate frictions. These frictions include more dollars per investor and loss of focus. The problem of more dollars per investor is that firms with more money may spent it on hiring more junior staff or nontraditional professionals which leads to lower returns than if the money was not spent or was better spent on hiring more senior staff (Charles River Venture in the early 2000s). The problem of loss of focus due to increasing scope comes from dealing with new situations and straying from their original expertise (Hicks, Muse, Tate & Furst (HMTF) in the later 1990s) (Lerner, Leamon, Hardymon 2012, 349, 361, 363). The costs of internal changes made when scaling up in size tend to be greater for smaller VC firms.[1] It is also difficult in the first place for these smaller VC firms to immediately raise a lot of money for a new fund unless they have a good reputation, strong past performance, or willing LPs, as shown

[1] When I say a VC firm is "bigger" or "smaller", I refer more to the amount of money a VC firm raises for a fund that tends to be "bigger" or "smaller". This way of describing a VC firm does not directly or necessarily refer to the assets under management of the VC firm itself. It is just clunky to keep saying "VC firm that tends to or has a track record of raising 'bigger' or 'smaller' funds."

by Gompers and Lerner (1998). Larger recent returns lead to larger capital commitments to subsequent new funds (Gompers and Lerner, 1998). Therefore, bigger VC firms, which have often reached that size due to already solid previous track records and more expansive networks, have an easier time scaling up than smaller VC firms. Surviving VC firms with continuing success often grow and scale up the size of their subsequent funds in a phenomenon called agglomeration. (Lerner, Leamon, Hardymon 2012, 349)

A fourth potential counterforce is the status quo bias, which is the tendency and preference for the current environment, situation, or way of things. Samuelson and Zeckhauser (1988) first introduced the term as they demonstrated the phenomenon through their decision-making experiments. The relevance of status quo bias in the SBVF context is that VC firms may prefer the comfort of staying with what they had been doing around that point in time instead of easily letting themselves be swept away by outside forces.

II.A.i.b Demand Side Perspective

VC firms, like any entity in business, should also be considering the perspective of their clients for staying competitive in the industry. The clients here are the startups/entrepreneurs themselves. Above, I have discussed what one might call a "cost-benefit analysis" that considered the potential tendency of VC firms to mimicking SBVF's strategy due to behavioral and herding factors with counterforces due to potential agency costs, real and operational costs, and status quo bias. This "cost-benefit" analysis is the supply side view, or done from the perspective of VC firms. It is important to discuss the demand side perspective, which is what follows.

Gompers (1995) says that venture capitalists believe their nonmonetary services are just as important as the monetary funding they provide for their portfolio companies, while many entrepreneurs believe that venture capitalists provide little more than money. Meanwhile, Lerner, Leamon, and Hardymon (2012) claim that entrepreneurs generally seek VC funding in the first place because they expect VC organizations to add value to their companies through things like advice, governance, and meddling, in exchange for giving up some company ownership (Lerner, Leamon, and Hardymon 2012, 56). No matter what one believes about what entrepreneurs believe about the nature of VC firms' services, it is important to keep in mind that especially in the current SBVF and technology-focused environment, entrepreneurs may weigh money more heavily in their ultimate decisions on which VC firms' offers to accept. Historically in past environments that experienced technology bubbles, we see that VC firms supplied more money and less expertise (Cumming 2010, 487). As SBVF, and perhaps increasingly other mega funds, pitch money at entrepreneurs instead of the other way around, it is plausible to imagine that bigger VC firms with more money might attract entrepreneurs more, holding all else (such as VC firms' potential for adding non-monetary value through advice and governance) relatively equal. In summary, this paragraph argues for the validity of my assumption that on the demand side, under the current SBVF environment, entrepreneurs primarily weight money over nonmonetary support from VCs in deciding what VC firms' offers to take.

II.A.iii Bringing Factors Together

Now, taking both the supply side cost-benefit analysis and the demand side factors into account, we can form our first hypothesis. Bigger VC firms should succumb more to the mostly behavioral forces that entice them to follow SBVF's strategy; in other words, raise bigger funds. Bigger VC firms have more assets and resources and reputation-wise will usually have a longer strong track record to fall back on if things do go wrong. Bigger VC firms may be able afford more risk and/or the potential operational and reputational costs of following a SBVF strategy.

Also, older and larger organizations simply attract more capital from LPs. (Gompers and Lerner, 1998)

On the other hand, smaller firms may face stronger headwinds in attempts to scale up, raise funding from LPs, and follow SBVF's strategy while also face more threatening damages if the strategy goes wrong. Therefore, smaller VC firms, or those in my "middle" and "low" sized sample, would most likely not scale up in size. If VC firms were to make any significant change in size for subsequent funds, it is easier to scale down than to scale up. This hypothesis is summarized below.

> *Hypothesis H1: In looking at intensive margin effects, bigger mega incumbent VC firms who invest in SoftBank industries will raise significantly larger subsequent funds, while small and medium sized incumbent VC firms would most likely see nonpositive abnormal change in subsequent fund size.*

In forming a hypothesis for intensive margin effects, but now along the dimension of funds' industry focus, all of the above discussion of factors remains relevant; all that is missing is to address the costs of VC firms changing investment industry focus for subsequent funds as part of the supply side cost-benefit analysis, which I will do now.

First, let us focus on middle and lower sized VC firms. These firms may have mixed and conflicting reactions in regard to taking the action of shifting away from their original industries of focus in investments. As a follow up to previous discussion, lower to middle sized VC firms most likely would not scale up in size in response to the entrance of SBVF. The question is what reaction, if any, would these firms have to SBVF?

In the new environment formed under the Vision Fund, smaller VC firms debate whether to change their pre-Vision Fund strategies to predict the best path forward to maintain previous or seek higher returns. As aforementioned, it is difficult for smaller VC firms to quickly raise a lot of money for a new fund, so given capital constraints, they may be forced to simply maintain or narrow the scope of their investments to become more specialized. A complement of specialization in smaller VC firms is greater focus toward on non-monetary support and guidance. Specialization allows VC firms to take greater risks in the investment in startups that require more expertise and attention (Sapienza, 1992). Smaller VC firms usually hold earlier stage investments, which require more of this nonmonetary effort on the VC firms' part (Cumming 2010, 486). These smaller VC firms also often have the comparative advantage of identifying investment opportunities at an earlier stage than larger competitors investing in more later stage companies (Hossain, Marinova, and Siddiqui, 2016). In addition, in the SBVF context, when smaller VC firms cannot compete with bigger ones in chasing the size of SBVF to mimic its money-throwing strategy, their comparative advantage is once again in specializing and offering more non-monetary than monetary support.

An alternative strategy to specialization in the SBVF environment is to shift the focus of their investment to other industries. Considering the demand side factor of entrepreneurs perhaps weighing monetary support over nonmonetary support, smaller VC firms may want to do so because they do not see themselves surviving by investing in technology portfolio companies in the environment of SBVF where so many VC firms also investing in primarily tech companies may have the advantage of bigger fund size and more money. However, as touched on before, shift or loss in focus can be very costly and challenging for even very experienced venture capitalists as they attempt to transfer skills that made them successful from area to another (Lerner, Leamon, Hardymon 2012, 361). Other consequences of shifting focus include losing or loosening original networks and the risk of confusion and reputation losses within the VC industry.

The direction and magnitude of the results of the tug-of-war smaller VC firms may face between specialization and investment industry focus shift depends on the extent of SBVF's influence on the U.S. VC industry and is uncovered through analysis. Given the aforementioned information, there exists no clear prediction regarding direction and extent of change in industry focus among what I categorize as small and middle sized firms.

Now, let us focus on bigger VC firms. My prediction is that they either maintain or increase their industry focus toward tech. Bigger VC firms are usually already more generalist and technology-focused, and thus will not need to shift anyway. Bigger VC firms also may not struggle as much as smaller VC firms would when given the opportunity to invest in companies in any industry. Following the logic for bigger and "mega" size category funds described in process of forming the fund size hypothesis, funds that are capable of doing so may tend to follow in SBVF's footsteps and invest in technology and other industries in which SBVF is interested. Thus, if not investing primarily in those industries before, bigger VC firms would want to now.

> *Hypothesis H2: In looking at intensive margin effects, bigger mega incumbent VC firms who invest in SB industries will see nonnegative shift investment focus into technology and other SBVF-interested industries, while small and medium sized incumbent VC firms see no clear prediction regarding direction and magnitude of any change in industry investment focus.*

II.A.ii Extensive Margin

Extensive margin effects study changes in our dependent variables in the U.S. VC industry through looking at first-time funds raised before and after the SBVF announcement. About fund size, I predict that first funds became increasingly larger in size after the first official press release about SBVF. The first reason is due to behavioral reasons leading to a "follow the crowd effect," as described in the previous "Intensive Margin" section. A second reason is that it is easier for VC firms to scale subsequent funds down rather than up, again due to challenges of growth outlined in the previous section. Therefore, VC firms may act to raise a first fund to be as big as possible in their environment at the time.

In the past few years, there has been increasing inflow of capital into private equity, as mentioned in the "Introduction," so any challenges to raising a big fund would not be primarily due to lack of investor capital. Rather, it is important to remember that an obstacle to raising money from LPs for a large first fund is the lack of resources, a previous track record, or reputation, as argued by Kaplan and Schoar (2005). If the phenomenon of bigger first funds is observed in the presence and influence of SBVF, one educated guess would be that this phenomenon is driven by seeing the larger first funds founded by experienced venture capitalists with strong reputations who perhaps split or left previous VC partnerships to start fresh. In other words, these VC firms raising their first funds may be founded by people such as GPs or entrepreneurs who already had track records and significant credibility through their previous work.

> *Hypothesis H3: In looking at extensive margin effects, funds all across the board, no matter the size category, will collectively see increased fund size after the first released announcement about SBVF. In other words, we will see positive change in fund size in small, middle, and mega size category first-time VC funds.*

About industry shift, I predict that first funds increasingly shifted out of investing in technology and other SB-interested industries after the first official press release about SBVF. This prediction stems from the "barriers to entry" idea in the industrial organization literature (Bain 1956) (Gilbert 1989), which relates to challenges firms face when they first try to enter and establish themselves in a market. Some barriers to entry new VC firms may face when seeking to invest in technology companies in the VC industry include product differentiation of incumbents and competition due to the number of competitors. Research on the product differentiation of incumbents (Bain 1956) (Schmalensee 1982) implies that incumbent VC firms, which invest mainly in technology, have advantages in the sense that they have already had a head start in developing a unique track record, which leads to "brand" identification, client loyalties, and reputation in that area, which are very important in the world of PE. Next, the number of competitors in an industry has an inverse relationship with profits or returns in more competitive markets. Thus, if VC firms established after the first official SBVF announcement observe and are aware of the SBVF's dominating influence and the growing trend toward investing in startups in the technology and other SB-interested sectors, they would recognize rising barriers to entry to having investment focus in technology industries and instead lean toward focus in non-SB-interested industries. (McAfee, Mialon, and Williams, 2004)

However, a counteracting force against VC firms investing with little hesitation in non-technology and thus non-SB-interested industries is that again, due to agency theory, VC firms should tend to invest in companies such that they can provide the most value in reducing asymmetric information through oversight and monitoring (Gompers 1995). These companies tend to be in industries with strong growth opportunities and high R&D intensities, which are more commonly characteristics of technology companies. In the presence of SBVF, though, this counteracting force may not be as strong as the barriers to entry forces.

Hypothesis H4: In looking at extensive margin effects, funds all across the board, no matter the size category, will collectively see shift away from technology and other SB-interested industries after the first released announcement about SBVF. In other words, we will see industry focus away from technology and other SB-interested industries in small, middle, and mega size category first-time VC funds.

Table 1 displays my hypothesis in order of presentation and in a more understandable format.

All in all, this paper aims to look at how VC firms in different size categories will react to the current heavily SBVF-influenced venture capital environment. VC firms may have multiple options at their disposal in their reactions, but the option of interest in this paper is (1) changes in fund size, as well as (2) the potential shift away from industries saturated with SBVF money toward those with less. This paper seeks to take first steps toward learning about the extent and channels through which SBVF may influence and disrupt the U.S. VC industry.

III. DATA AND EMPIRICAL METHODS

SECTION III.A: DATA AND METHODS

The focus of this project is on Softbank's effect on aspects of the United States venture capital landscape. I focus on the U.S. because it has the best combination of having the one of the biggest VC industries as well as the most reliable and longstanding data. Figure E in the Appendix shows VC funds by global region, where North America accounts for the largest portion of funds and a large portion of North American funds are those of the U.S. I screen for the data I want in Thomson VentureXpert through SDC Platinum software. VentureXpert, one of the most longstanding databases for characteristics of venture capital funds, investments, portfolio companies, began collecting data in 1961 and is a unit of Thomson Reuters. Kaplan and Lerner (2016) discuss VentureXpert in detail. Only one database is used for analysis because merging multiple databases would not be practical due to lack of common fund or firm identifiers in venture capital data. VentureXpert is chosen over other databases for many reasons. For instance, compared to Venture Source, another longstanding database that began collecting data in 1994 and is a unit of Dow Jones, VentureXpert has more complete investment data coverage, which is important for investigating the question at hand. The year range of the dataset I use and clean for analysis is 2011 to 2019. Raw data collected that directly enters into analysis includes: VC fund initial closing date, VC fund size (in USD millions), industry class of each VC fund's portfolio companies (both the (1) main industry class and (2) industry subgroup), VC fund stage (balanced, early, later, seed), and VC firm founding date.

I use a difference-in-differences causal methodology for this question. This methodology requires me to use already-established VC firms and newly-established firms in doing analysis on intensive and extensive margin effects, respectively. I define already-established VC firms as firms that raised at least one fund before the cutoff date and that raised at least another fund after cutoff. My cutoff date is the date on which SoftBank released its first major public disclosure about its Vision Fund. The date of the first official disclosure, about the presence and potential size of the Vision Fund, is October 14th, 2016. I run my set of regressions with this date as the cutoff. In doing analysis, I classify fund year by fund initial closing date year. The disclosure announcements here are exogenous events that are assumed to not be anticipated by other VC firms, so it allows the identification of causal effects. In the newly-established firm analysis, only first-time funds are used. And in terms of how quickly VC firms might react to the SoftBank disclosures in raising funds, Figure F in the Appendix shows that the average time a VC fund reaches its first close in the U.S. has been consistently around 6 months in recent years.

The difference in differences method can take care of concerns about agglomeration, dry powder, increasing influence of angel investors and crowdfunding, and limited partners or investors increasingly jumping in to invest in private markets more when they used to invest more in the public markets, as potential factors in changes in fund size, because I assume these concerns are common to all VC firms and not solely to firms focused on investing in particular industries pre-cutoff. I am also assuming here that there are no significant differences that would affect the analysis in this paper between VC firms that back technology vs. non-technology startups, between investors that choose to invest in technology focused VC funds over non-technology focused VC funds, and between what entrepreneurs starting their business in technology vs. not technology look for when considering venture capital funding.

Another aforementioned unique aspect of the SoftBank Vision Fund is that Saudi Arabia's Public Investment Fund (PIF) is a huge "lead investment partner," funding up to 45 billion USD of the Vision Fund. To take this aspect into account in analysis, I did research on the

PIF and found that the biggest development in the time period observed for analysis may be that the Saudi Arabia Council of Economics and Development Affairs (CEDA) launched a PIF Program on April 24th, 2017. This PIF Program is meant to further strengthen the already-existing PIF. This launch date happens to be close to the date of the second major SoftBank announcement about the Vision Fund on May 22nd, 2017 about the Vision Fund's first major closing size of almost 100 billion. Together they represent exogenous shocks related to SoftBank's influence. These factors should be kept in mind when looking at the results of regressions on outcomes in the post-cutoff years, such as of 2017 and 2018, individually.

In the difference-in-differences regression models, my time variable is a dummy variable that equals 1 if a VC fund has initial close after the cutoff date and 0 if before or on the cutoff date.

In my design, treatment group classification relies on knowing VC funds' industry focus. As mentioned above, VC funds that have an industry focus in SoftBank Vision Fund's industries of focus, or broadly technology, I call either "SoftBank industry" or "SBVF industry" funds. I determine a "SoftBank industry" based on the thorough description stated in SoftBank's May 22nd, 2017, disclosure. I decide to include technology, or Thomson's main industry class of information technology (IT), as well as the subgroup industries of "consumer-related," "financial services," "transportation," and "business services." Table B gives the Thomson database list of industry classifications for portfolio companies. For VC funds investing in mostly non-SoftBank industry companies, I call "non-SoftBank industry" funds.

To determine whether to classify VC funds as "SoftBank industry" funds or "non-SoftBank industry" funds, I looked at the ratio of number of "SoftBank industry" portfolio companies to "non-SoftBank industry" portfolio companies within a fund. If this ratio was greater than 0.5, I would classify the fund as a "SoftBank industry" fund. If this ratio was less than 0.5, I would classify the fund as a "non-SoftBank industry" fund. If the ratio was exactly 0.5, I would drop the fund to ensure the cleanest analysis possible. Dropping funds brings up the potential concern of losing data, but it is not a huge concern here because not many funds are dropped for having an exact 0.5 ratio.

The treatment and control groups are straightforward for both the already-established firm analysis and the newly-established firm analysis. The treatment group generally refers to an industry focus on "SoftBank industries." The control group generally refers to an industry focus on "non-SoftBank industries." The treatment group is appropriate because non-Softbank industry funds should not be directly affected by SoftBank's presence. There is only one slight difference between the already-established and newly-established firm analysis. The newly-established firm analysis, since it only considers a firm's first-time funds, automatically classifies any "SoftBank industry" fund as belonging to the treatment group and any "non-SoftBank industry" fund as belonging to the control group. However, for already-established firm analysis, I classify firms as belonging in the treatment or control group based on the industry focus of the funds these firms raised in the pre-cutoff period. I do this because the already-established firm analysis utilizes the difference-in-difference model to compare the outcomes of interest of funds between the pre-cutoff and post-cutoff period for each firm, where each firm serves as one unit of observation.

For already-established firm analysis, again, I classify firms as belonging in the treatment or control group by looking at the funds these firms raised in the pre-cutoff period of 5 years. I considered two different methods. The first method was just to take the industry focus of the pre-cutoff fund closest to the cutoff date. The second method is to take average industry focus of all the pre-cutoff funds raised by a VC firm. (See Figure G in the Appendix for the distribution of

"Treatment" group classification for these two methods.) I am choosing the second method because I believe it better represents the general/overall trend/behavior of the VC firm. Figure G shows that there is not too much difference between the 2 methods.

I went through the same dilemma of choosing one of two methods for classifying/categorizing funds into size channels for analysis, where my final chosen methodology was to take the average fund size of all the pre-cutoff funds raised by a VC firm. (See Figure H in the Appendix.) My analysis for the question explored in this paper is done through separate size channels; again, the size categories are "lower market," "middle market," and "mega." I will define "mega" funds as having a size of larger than 500 million, which happens to represent the largest 10% of the funds in the data, "lower market" funds as having sizes of 50 million or lower, the smallest 50% of the funds, and remaining funds as "middle market" in size. In this analysis, I do not use the common cutoff of 1 billion (Pitchbook) or larger to label funds as "mega" because this cutoff is too high and thus does not give enough data for results in difference-in-difference "mega" size analysis.

For my fixed effects and controls, I use year dummies, inflows into VC, fund stage of development, and experience of each VC firm. I control for these factors due to discussion and findings in (Kaplan and Schoar 2005), (Gompers, Kovner, Lerner, and Scharfstein 2008), and (Gompers, Kovner, and Lerner 2009). I take data for quarterly and yearly inflows into U.S. VC over time from Preqin. I use quarterly inflow data for already-established firm analysis and yearly inflow data for newly-established firm analysis due to the nature of the regression models. For yearly inflow, I exported values under "Historical Fundraising" straight from the website. However, since the website did not go as far back as I desired for the quarterly inflow values, to get quarterly data going back to 2011 in order to use a 5-year pre-cutoff period for my analysis, I needed to take some extra steps to manually calculate quarterly inflow. These extra steps entailed using advanced search to export all funds in the Preqin database that were labeled as having the "Venture Capital" strategy and "Fund Manager Location" of the United States. Once all these funds' data was exported to Excel, I made a pivot table to calculate the aggregate value of these funds' final close sizes by quarter. Fund stage of development represents values such as "Early," "Seed," "Later," and "Balanced." For the VC firm experience control, the number of funds raised in the pre-cutoff period, starting with 2011, in the dataset is taken. I define firm experience this way, rather than perhaps the more intuitive definition of number of funds raised over a VC firm's entire lifetime, because I believe that VC firms that raise more funds in the years closest to the cutoff have more relevant and informative priors when making decisions upon the entry of SBVF than those who may have raised more funds but longer before October 14, 2016. I considered including controls for dry powder, but that data only exists on the industry level and may interfere with some other controls, such as year dummies. I calculate robust standard errors, clustering by time.

Tables 2 and 3 provide broad summary statistics on the already-established and newly-established VC firm datasets used for analysis. Tables 4 and 5 provide deeper summary statistics for the already-established and newly-established VC firm datasets along the dimensions of size channel and year. Figure 1 provides a summary statistic figure that displays the distribution of fund size within the data used in this study. Figures 2 and 3 provide a summary statistic figure that displays the distribution of funds by year, size channel, and industry focus within the already-established and newly-established datasets, separately.

SECTION III.B: SUMMARY STATISTICS

For the purposes of interpreting later results, the summary statistics here are only on the cleaned datasets used for regression analysis. I cleaned the original dataset by deleting observations that couldn't be used in analysis, such as if no values existed for fund closing dates or if data was missing on the industry focus of a fund's portfolio companies.

[REFER TO TABLES 2-5 AND FIGURES 1-3 IN SECTION VI]

In Figure 1, which is the distribution of fund size within the full set of cleaned data used in my analysis before I separate into already-established VC firms and newly-established VC firms, the cutoffs that separate funds into size categories are marked by vertical red lines. It is clear that the vast majority of VC funds are small in size, raising funds of 50 million USD or lower. Again, Figure 1 shows that "mega" funds represent the largest 10% of the funds in the data, "lower market" funds represent the smallest 50% of the funds, and remaining funds as "middle market" in size.

Table 2, Tables 4A, 4B, and 4C, and Figure 2 convey summary statistics on the already-established VC firm dataset I use for intensive margin analysis. First, Table 2 shows that the dataset used for intensive margin analysis has 354 funds over the 2011-2019 time range. The percentage of SBVF-industry investments in one fund was about 80%, on average over all 812 funds. About 80% of these 354 funds held majority SBVF-industry investments. The 354 funds were split about 50-50 in terms of having initial closes before or after the cutoff of October 14, 2016. The average U.S. quarterly inflow into, or aggregate capital raised in, VC was a little more than 10,000 million USD. Finally, VC firms experience, defined in this paper as the number of funds raised by a VC firm from 2011 to the cutoff, averages around 2.

Breaking down the intensive margin dataset even more are Tables 4A, 4B, and 4C, as well as Figure 2. In Table 4A, which gives statistics by size category, 123 out of the 354 total funds, or about 35% of VC firms in the dataset are categorized as “low” size. Approximately 93% of these funds held majority SBVF-industry investments. Next, 174 out of the 354 total funds, or about 50% of VC firms in the dataset are categorized as “middle” size. Approximately 76% of these funds held majority SBVF-industry investments. Finally, 57 out of the 354 total funds, or about 16% of VC firms in the dataset are categorized as “mega” size. Approximately 81% of these funds held majority SBVF-industry investments.

In Table 4B, which gives statistics by year, the number of funds increased significantly around 2013 in the 2011-2019 time range. The percentage of funds each year that hold majority SBVF-industry investments fluctuates in the range of 70-95%.

In Table 4C, which gives statistics by both size category and year, the number of funds generally increases over the 2011-2019 time range, and in each of these size category-year groups, the average percentage of funds that hold majority SBVF-industry investments decreases very slightly over these years. Figure 2 is a stacked bar chart that serves as a visual representation of Table 4C.

Tables 3, 5A, 5B, 5C, and Figure 3 convey summary statistics on the newly-established VC firm dataset I use for extensive margin analysis. First, Table 3 shows that the dataset used for extensive margin analysis has 812 funds over the 2011-2019 time range. The percentage of SBVF-industry investments in one fund was about 81%, on average over all 812 funds. About 83% of these 812 funds held majority SBVF-industry investments. Of the 812 funds, about one-third have their initial close before the cutoff of October 14, 2016, while the remaining two-thirds have their initial close after the cutoff.

Breaking down the intensive margin dataset even more are Tables 5A, 5B, and 5C, as well as Figure 3. In Table 5A, which gives statistics by size category, 472 out of the 812 total funds, or about 58% of VC firms in the dataset are categorized as "low" size. Approximately 85% of these funds held majority SBVF-industry investments. Next, 311 out of the 812 total funds, or about 38% of VC firms in the dataset are categorized as "middle" size. Approximately 81% of these funds held majority SBVF-industry investments. Finally, 29 out of the 812 total funds, or about 4% of VC firms in the dataset are categorized as "mega" size. Approximately 78% of these funds held majority SBVF-industry investments.

In Table 5B, which gives statistics by year, the number of funds generally increased around 2014 in the 2011-2019 time range, with the highest levels in the 2014-2018 years. The percentage of funds each year that hold majority SBVF-industry investments fluctuates in the range of 80-90%, which exhibits less variance than for the intensive margin analysis dataset.

In Table 5C, which gives statistics by both size category and year, the number of funds fluctuates over the 2011-2019 time range for each size category. For the "low" size category, the number of funds each year fluctuates in the range of 30-73. For the "middle" size category, the number of funds each year fluctuates in the range of 21-51. For the "mega" size category, the number of funds each year fluctuates in the range of 0-7. In each of these size category-year groups, similar to the intensive margin analysis dataset, the average percentage of funds that hold majority SBVF-industry investments generally fluctuates in the middle-high end of the 50-100% range. Figure 3 is a stacked bar chart that serves as a visual representation of Table 5C.

SECTION III.C: DIFFERENCE-IN-DIFFERENCES VALIDITY

To show the validity of my use of the difference-in-differences methods, I do two things. First, I show that the parallel trends assumption holds. Second, in repeated cross sections, the composition of the sample should stay constant between periods.

For first showing that the parallel trends assumption holds, see Figure 4 for selected event study graphs for both already and newly established VC firms for fund size and industry shift. Figure 4 shows only the four middle size category graphs. There are a total of three to four graphs for each of these four analyses because analysis is separated by size channel. To see event study graphs for all 14 separate channels of analysis, see Figure I, J, K, L in the Appendix.

[REFER TO FIGURE 4 IN SECTION VI]

Next, it is shown that the distribution of certain characteristics of my cleaned data sample should be similar for pre-treatment and post-treatment periods, such as for distribution of funds investing in portfolio companies of different stages, as shown in Figure M for years 2011-2019.

[REFER TO FIGURE M IN SECTION VI]

SECTION III.D: EMPIRICAL DESIGN

SECTION III.D.i: Regressions for Fund Size

In analysis, the empirical designs rely on the difference-in-differences methodology. For already-established VC firms, I run 3 regressions, one for each of the size channel categories of low, middle, and mega. More specifically, for each size channel category, I run the regression on each separate category dataset. The regression equation is as follows:

$$SIZE_{ist} = \mu + \gamma \cdot D_s + \alpha \cdot D_s T_t + \delta_t + \omega_i + X_{ist} + \varepsilon_{ist}$$

where $SIZE_i$ is fund size in millions of US dollars, T_t is a dummy that equals 1 for funds raised after a cutoff and 0 if before the cutoff, D_s is a dummy that equals 1 if the VC fund invested in same industries as Softbank (broadly, "technology") before the cutoff, 0 if not, δ_t represents year dummies, ω_i represents firm dummies, and X represents controls (inflows into VC, fund stage, and firm-specific experience). Due to potential collinearity issues, I do not include both the T_t dummy on its own and the δ_t year dummies in this regression equation. I do not include firm fixed effects in this regression because I assume that there are few differences among firms that would significantly affect my results. The only significant result-affecting firm difference I identify is the sophistication of VC firms regarding the environment of the years immediately around SBVF's entry. This difference I account for through my own definition of VC firm experience as I described earlier. The regressions are run using robust standard errors, clustering by time.

For newly-established VC firms, I run 4 regressions, one for each of the size channel categories of low, middle, and mega, and also one on the overall dataset that is not split into size categories. The regression equation is as follows:

$$FUNDSIZE_{ist} = \beta_0 + \beta_1 \cdot TREAT_s + \beta_2 \cdot POST_t + \beta_3 \cdot TREAT_s POST_t + X_{ist} + \varepsilon_{ist}$$

where $FUNDSIZE_i$ is the average fund size raised for treatment or control group in a certain year, $POST_i$ is a dummy that equals 1 for funds raised after the cutoff and 0 if before, $TREAT_i$ is a dummy that equals 1 if the VC fund invested in same industries as Softbank (broadly, "technology"), 0 if not, and X represents controls (inflows into VC). It is not possible to implement firm fixed effects here because the regression is run on a collapsed dataset, and time fixed effects in the form of year dummies are not appropriate for inclusion here due to the collapsed dataset and sparse amount of data. The regressions are run using robust standard errors.

For my newly-established firm analysis, which I run with collapsed data, I tried both simple DiD and event study regressions/analysis. However, due to lack of data, I had to rely on simple DiD in looking at industry shift and fund size changes.

SECTION III.D.i: Regressions for Industry Shift

In analysis, the empirical designs rely on the difference-in-differences methodology. For already-established VC firms, I again run 3 regressions, one for each of the size channel categories of low, middle, and mega. The first differences regression design is as follows:

$$INDSHIFT_s = u + \alpha \cdot D_s + \delta_t + X_{ist} + \Delta\varepsilon_{is}$$

where $INDSHIFT_s$ is the difference between the post-cutoff and "pre-cutoff percentage" of VC firm's deals that are in "SoftBank" industries, D_s is a dummy that equals 1 if the VC fund invested in same industries as Softbank (broadly, "technology") before the cutoff, 0 if not, δ_t represents year dummies, and X represents controls (inflows into VC, fund stage, and firm-specific experience). For $INDSHIFT_s$, the post-cutoff percentage is calculated as the average percentage of all the funds a firm raised in the post-cutoff percentage. I also run regressions on the post-cutoff percentage in the specific year of 2018, as well as for 2017 for the first cutoff of October 24th, 2016. The "pre-cutoff percentage" is the percentage of portfolio companies in the pre-cutoff fund closest to cutoff that were in "SoftBank" industries. The regressions are run using robust standard errors, clustering by time. Firm fixed effects, if I were to include them, are differenced out and thus not included here.

For newly-established VC firms, I again run 4 regressions, one for each of the size channel categories and one on the overall dataset. The regression equation is as follows:

$$NUMFUNDS_{ist} = \beta_0 + \beta_1 \cdot TREAT_s + \beta_2 \cdot POST_t + \beta_3 \cdot TREAT_s POST_t + X_{ist} + \varepsilon_{ist}$$

where $NUMFUNDS_i$ is the number of funds raised for treatment or control group in a certain year, $POST_i$ is a dummy that equals 1 for funds raised after the cutoff and 0 if before, $TREAT_i$ is a dummy that equals 1 if the VC fund invested in same industries as Softbank (broadly, "technology"), 0 if not, and X represents controls (inflows into VC). It is not possible to implement firm fixed effects here because the regression is run on a collapsed dataset, and time fixed effects in the form of year dummies are not appropriate for inclusion here due to the collapsed dataset and sparse amount of data. The regressions are run using robust standard errors.

Again, for my newly-established firm analysis, which I run with collapsed data, I tried both simple difference-in-differences (DiD) and event study regressions/analysis. However, due to lack of data, I had to rely on simple DiD in looking at industry shift and fund size changes.

IV. RESULTS

Tables 6, 7, C, D, and E display regression results for analysis for VC firms in terms of fund size. Table 6 provides in one table all the results for already-established firms across the 3 different size channels as well as includes regressions that focus only on industry shift in the specific years of 2017 and 2018. Tables C, D, and E in the Appendix provide results for each size channel category separately for already-established firms, with different combinations of including and taking out controls to observed their effect on results. These regressions are run on all post-cutoff funds in the year range 2017-2019. Table 7 is analysis for newly-established VC firms.

Tables 8, 9, F, G, and H display regression results for analysis for VC firms in terms of industry shift. Table 8 provides in one table all the results for already-established firms across the different size channels. Tables F, G, and H in the Appendix provide results for each size channel category separately for already-established firms, with different combinations of including and taking out controls to observed their effect on results. These regressions are run on all post-cutoff funds in the year range 2017-2019. Table 9 is analysis for newly-established VC firms.

As is apparent from observing the event study graphs in Figure 4, as well as the entire body of graphs in Figures I, J, K, and L in the Appendix, the parallel trends are not perfect in this analysis.[2] Since parallel trends is a key assumption that must hold for the most accurate and reliable analysis, the analysis in this paper may not be as strong as it would be under circumstances in which better parallel trends exist. In addition, given my already flexible size

[2] I also noticed a possible lag in control group trends, in the sense that they would be a bit more parallel with treatment group trends if the control group trends were shifted to the left one year.

category cutoff for mega size funds, there was not enough data to run regressions for the newly-established mega fund size analysis for both dependent variables of industry shift and fund size.

[REFER TO TABLES 6-9 IN SECTION VI]

Now, regarding the results for the already-established firms and the dependent variable of fund size in Table 6, the magnitude of these coefficients represents the change in the size of VC funds from pre-cutoff to post-cutoff in millions of USD, attributed to SBVF entry. None of the coefficients in this channel of analysis are significant at a confidence level of 90%. Negative coefficients imply a decrease in fund size due to the entry of SoftBank Vision Fund, and positive coefficients imply an increase in fund size due to the entry of SoftBank Vision Fund. In general, again, larger magnitudes of coefficients should be interpreted as SoftBank Vision Fund having a stronger effect on changes in fund size.

For low size funds, the coefficients are positive. When taking fund size change for from before SBVF to the period of all post-cutoff years of 2017-2019, the coefficient is 27.79. Funds that initially closed in 2017 saw a 0.80 coefficient, while funds that initially closed in 2018 saw a 3.29 coefficient. In summary, VC firms that had for the most part raised low-size pre-cutoff funds increased the size of their post-cutoff funds. The increase in fund size was gradual, where fund size increase in 2018 was four times the increase in 2017. Then, the increase in fund size was so great in 2019, as seen in Figure I in the Appendix, that the coefficient for all VC funds with initial closes in 2017-2019 was more than 8 times the coefficient for just 2018 VC funds.

The coefficient for middle size funds is positive with 17.82 for the post-cutoff funds taken all at once (for all post-cutoff years of 2017-2019), and is positive for 2017 and negative for 2018 taken separately with coefficients of 10.9 and -22.13, respectively. In summary, VC firms that had for the most part raised middle-size pre-cutoff funds increased the size of their post-cutoff funds, though there was a size decrease in 2018. As seen in Figure I in the Appendix, the increase in fund size was so great in 2019 that the coefficient for all VC funds with initial closes in 2017-2019 was greater than the positive coefficient for 2017, even with the negative coefficient in 2018 of more than 2 times the magnitude of the 2017 coefficient.

The coefficients for the mega size funds are negative for 2017 and 2018 taken separately, with -1288 and -693.6, respectively. The coefficient for mega size funds over the whole post-cutoff period of 2017-2019 is positive with 453.7. In summary, VC firms that had for the most part raised mega-size pre-cutoff funds decreased the size of their post-cutoff funds in 2017 and 2018, with the greater decrease in size in 2017. The positive coefficient for mega size funds over the whole post-cutoff period of 2017-2019 is potentially due to a great "increase" in fund size in 2019 due to no funds raised in 2019 by VC firms categorized as non-SBVF industry firms by their pre-cutoff track record.

In looking at the effects of different combinations of controls on the coefficient of interest across the size channel categories of low, middle, and mega out of curiosity through Tables C, D, and E in the Appendix, the sign of the coefficients is mostly consistent with the regressions run with all the controls, and the magnitude of coefficients do not vary within a wide range.

All in all, we generally see nonsignificant and varying results across all three size categories. Low size funds see positive size change and mega size funds see negative size change in 2017 and 2018. Middle size funds see positive size change in 2017 but then negative change in 2018.

Now, regarding the results for the newly-established firms and the dependent variable of fund size in Table 7, all coefficients are positive and nonsignificant. Again, the magnitude of these coefficients represents the change in the size of VC funds from pre-cutoff to post-cutoff in millions of USD, attributed to SBVF entry. Like for Table 6, these positive coefficients imply an increase in fund size due to the entry of SoftBank Vision Fund. In general, again, larger magnitudes of coefficients should be interpreted as SoftBank Vision Fund having a stronger effect on changes in fund size.

For low size funds, the coefficient is 4.55. For middle size funds, the coefficient is 32.22, a magnitude about 7 times that of low size funds. For the mega size analysis, no coefficients were available due to not enough data with the size cutoffs I set for my analysis. I also run an "overall" regression over all the funds pooled together, regardless of size category, and the positive coefficient is 36.15.

In summary, newly-established VC firms generally increased the size of their first-time funds after SBVF entry. Including controls in this newly-established analysis for fund size does not change the coefficients but does reduce the standard errors, except for in the "overall" regression where controls very slightly increased standard errors.

Now, regarding the results for the already-established firms and the dependent variable of industry shift in Table 8, the magnitude of these coefficients represents the change in the percentage of a funds' portfolio companies that were in SBVF industries from pre-cutoff to post-cutoff, attributed to SBVF entry. Negative coefficients imply that VC firms are shifting away from investing in portfolio companies in industries that overlap with SoftBank's industries of focus, while positive coefficients imply VC firms moving toward companies in SoftBank industries of focus. In general, larger magnitudes of coefficients should be interpreted as SoftBank Vision Fund having a stronger effect on industry shift.

For low size funds, the coefficients are negative. When taking industry shift for from before SBVF to the period of all post-cutoff years of 2017-2019, the coefficient is -0.03, though this coefficient is not significant. However, there is great significance when taking the funds with initial close in years 2017 and 2018 independently, which see coefficients with a p-value of less than 0.01. Funds that initially closed in 2017 saw a -0.44 coefficient, while funds that initially closed in 2018 saw a -0.05 coefficient. In summary, VC firms that had for the most part raised low-size pre-cutoff funds shifted away from investing in portfolio companies in industries that overlap with SoftBank's industries of focus. VC funds had the greatest significant reaction to SBVF's entry in 2017, with a magnitude of 0.44 of almost 9 times the significant reaction of funds in 2018.

The coefficients for the middle size funds are positive of around 0.06 for the post-cutoff funds taken all at once (for all post-cutoff years of 2017-2019), and they are stronger for 2017 and 2018 taken separately with coefficients of 0.2 and 0.16, respectively. The strongest significance (as well as reaction) is seen in 2017, though the coefficient is not significant enough with a p-value of less than 0.1 but greater than 0.05. In summary, VC firms that had for the most part raised middle-size pre-cutoff funds shifted toward investing in portfolio companies in industries that overlap with SoftBank's industries of focus. VC funds had the greatest significant reaction to SBVF's entry in 2017, with a magnitude of 0.2, though not quite reaching a p-value as low as 0.05.

The coefficients for the mega size funds are negative with significance. The coefficient of the post-cutoff funds taken all at once is -0.16, and the coefficients for 2017 and 2018 taken separately are -0.28 and -0.06, respectively. The strongest significance (as well as reaction) is seen in 2017 with a p-value of less than 0.01. In summary, VC firms that had for the most part raised mega-size pre-cutoff funds shifted away from investing in portfolio companies in industries that overlap with SoftBank's industries of focus. VC funds had the greatest significant reaction to SBVF's entry in 2017, with a magnitude of 0.28 of almost 5 times the significant reaction of funds in 2018.

In looking at the effects of different combinations of controls on the coefficient of interest across the size channel categories of low, middle, and mega out of curiosity through Tables F, G, and H in the Appendix, the sign of the coefficients is consistent with the regressions run with all the controls, and the magnitude of coefficients do not vary widely. It is interesting to note that Table H implies that VC firm experience seems to be a control that contributes to greatest significance in the coefficient for mega-size VC firms.

All in all, we generally see significant results across all three size categories, with the most significant results occurring when taking only VC funds with initial closes in 2017. Low and mega size funds see shifts away from SBVF industries, while middle size funds shift toward SBVF industries. The shift away from SBVF industries exhibited by low and mega size funds is more significant than the shift toward SBVF industries exhibited by middle size funds.

Now, regarding the results for the newly-established firms and the dependent variable of industry shift in Table 9, all coefficients are negative and nonsignificant. By nonsignificant, I mean that the coefficient p-values are greater than 0.1. The magnitude of these coefficients represents the change in the number of first-time VC funds focusing primarily on SBVF industry vs. non-SBVF industry firms, attributed to SBVF entry. Like for Table 8, the negative coefficients imply that VC firms are shifting away from investing in portfolio companies in industries that overlap with SoftBank's industries of focus. In general, again, larger magnitudes of coefficients should be interpreted as SoftBank Vision Fund having a stronger effect on industry shift.

For low size funds, the coefficient is -1.17. For middle size funds, the coefficient is -0.83, a magnitude slightly less than that of low size funds. For the mega size analysis, no coefficients were available due to not enough data with the size cutoffs I set for my analysis. I also run an "overall" regression over all the funds pooled together, regardless of size category, and the negative coefficient is -3.5.

In summary, newly-established VC firms generally increasingly raised their first-time funds in non-SBVF industries after SBVF entry. Including controls in this newly-established analysis for industry shift does not change the coefficients but does reduce the standard errors.

V. DISCUSSION

First, for the already-established VC firm analysis for the dependent variable of fund size (Table 6), results show increase in fund size for low size VC firms, increase then decrease in fund size for middle size VC firms, and decrease in fund size for mega size VC firms. To recap hypothesis H1, I expected that low and middle size VC firms would keep their post-cutoff fund sizes about the same or smaller than before, while mega size VC firms would increase their subsequent post-cutoff fund sizes. In this analysis, however, my results were mixed and did not match hypothesis H1 perfectly. All coefficients for this analysis, though, can be taken more lightly as they are not significant at a confidence level of 90%.

Low size category analysis shows slight (though nonsignificant) increase in fund size post-cutoff. Results show a small increase in 2017, then an only slightly bigger increase in 2018. Because these coefficients are nonsignificant, it does not seem that VC firms on average increase fund size on purpose or with concrete resolve. The increase may be a result of higher rate of agglomeration in SBVF industry VC firms than in non SBVF industry VC firms. Another thing is that in the SBVF environment, limited partners (LPs), the investors who provide the money for the funds, are also more willing to put their capital with funds of low size VC firms, so these VC firms actually have an easier time scaling up.

Middle size category analysis shows an increase in 2017, then a decrease in 2018 in fund size for middle size VC firms. Perhaps like for low size VC firms, increase in 2017 can be explained by (1) higher rate of agglomeration in SBVF industry VC firms than in non-SBVF industry VC firms, (2) stronger headwinds in scaling up, (though less than for low size firms), (3) LPs more willing to put capital with smaller VC firms in the SBVF environment. However, the decrease in 2018 is harder to explain. One explanation is that VC firms may realize after recovering from the immediate reaction to SBVF in 2017 that following SBVF in scaling up is a bad strategy. After recovering from the initial shock, middle size firms may realize that following the SBVF strategy to follow its perceived potential success is simply an impossible fantasy. The belief that they are unable to catchup to, attain, or even compete with a fund of SBVF's size and reputation may solidify in middle size VC firms' minds as a barrier to entry. Indeed, middle size VC firms may have become more clear headed in 2018 and have gained better situation awareness, a behavioral science concept.

Situation awareness refers to the perception of information and extent of understanding the most complete picture possible of a situation. Once the highest level of situation awareness is achieved, one has the ability to predict the course of future dynamics and events, which in turn facilitates relevant decision-making. The level of situation awareness one can achieve depends on the extent of working memory and attention, which can be limited and challenged especially in complex environments. (Endsley 1995)

The concept of situation awareness also explains why low size VC firms continued to increase fund size in 2018 after an initial reaction of increase in 2017 instead of making the better decision to stop and scale down. Lower size firms, in perhaps having also more lower size VC firms in mind as competitors than bigger ones, may not be able to fully realize or see or remember that there are also much bigger firms out there that have a lot more money to offer entrepreneurs and also pose a threat to success of lower size VC firms. In other words, middle size VC firms gained better situation awareness after initial immediate reaction in 2017 so that in 2018, it made a more rational decision to back away from continuing to increase fund size and follow SBVF strategy, while low size VC firms, with less contact with bigger VC firms and them not being as salient in their minds as closest competitors have not gained as much situation awareness and still act under a less realistic image about the world around them.

For mega size category analysis, results show decrease in fund size in both 2017 and 2018, which is the opposite of my initial hypothesis. Since bigger VC funds may not face as many frictions to scaling up compared to both low and middle size VC firms, the fact that they have scaled down in size reveals that these firms actively chose not to scale up despite having capability to do so. To explain this result, situation awareness is again an explanation that makes sense - mega size funds are almost directly competing with SBVF for LP investment and for attracting strong portfolio companies, so SBVF in their minds is a bigger threat and constructs a sort of "barriers to entry" force and thus mega size funds more strongly believe they can't catch up to SBVF and so take the opposite action.

Second, for the already-established VC firm analysis for the dependent variable of industry shift (Table 8), again, results show that the low and mega size categories see significant negative coefficients, while the middle size category sees positive coefficients. To recap hypothesis H2, I had no clear prediction about the direction and magnitude of the reaction that low and middle size VC firms would have to SBVF entry, while I predicted that mega size VC firms would have nonnegative coefficients or that they would shift toward SBVF industry investment. In this analysis, all size category results are consistent with my initial hypothesis H2 except for in the mega size category, which sees significant negative coefficients.

Low size category analysis shows that shift away from SBVF means that the strategy of changing industry focus was chosen over the strategy of specializing and staying within the SBVF industries. The magnitude of the coefficient captures the extent to which low size VC firms see SBVF as a threat. As explained in Section II, the threat comes from them not seeing themselves surviving in an environment where entrepreneurs with companies in SBVF industries may tend to weight money over non monetary support more, and where bigger VC firms can better afford to throw money at startups. Instead of staying and continuing to focus on SBVF industry portfolio companies for investment, low size VC firms are willing to bear the huge cost and challenge of shifting their industry of expertise more to non-SBVF industries.

Middle size category analysis results show that VC firms are staying in or slightly shifting toward more investment in SBVF industries, which implies that they see SBVF as less of a threat. From aforementioned reasons outlined in Section II, these results are most likely because as middle size VC firm funds have more assets than low size VC firm funds, their worry about an inability to attract and keep SBVF industry entrepreneurs and their startups is less than the large cost of shifting out of investment focus on SBVF industries.

For mega size category analysis, I hypothesized that post-cutoff mega funds would increase investment in SBVF industry portfolio companies, but results actually show a significant shift away. Since bigger VC funds are usually more generalist and do not have as much trouble shifting investment both into or out of a broad range of industries compared to smaller VC firms, these bigger firms actively chose to shift away from SBVF industry investments despite having the strongest capability to do so. Similar to the reasoning explained in the already-established fund size analysis, mega size VC firms' greater situation awareness allows them to realize the potential challenge of attempting to chase success through following SBVF's strategy. Again, mega size funds are almost directly competing with SBVF for LP investment and for attracting strong portfolio companies as the biggest funds in the U.S. VC industry otherwise, so SBVF is an especially salient and direct threat that constructs a sort of "barriers to entry" force. Thus, mega size funds may shift away from SBVF industries.

Third, for the newly-established VC firm analysis for the dependent variable of fund size (Table 7), results show positive coefficients. These results are consistent with hypothesis H3, which predicted seeing increased fund size in all size categories (small, middle, and mega) of first-time VC funds. The only thing here is that no results exist for mega VC firm analysis because the dataset does not record non-SBVF mega funds after 2016. Also, the coefficients for this analysis can be taken more lightly, as they are not significant at a confidence level of 90%.

This result supports the prediction that VC firms would follow their behavioral response and "follow the crowd" in trying to mimic and catch up to SBVF's size. This result also supports the possibility that VC firms will almost always seek to raise the biggest first-time fund possible, and that this desire was realized through the increasing amount of money flowing into the VC industry in the SBVF environment.

Fourth, for the newly-established VC firm analysis for the dependent variable of industry shift (Table 9), results show negative coefficients. These results are consistent with *hypothesis* H4, which predicted seeing industry focus shift away from SBVF industries in all size categories (small, middle, and mega) of first-time VC funds. The only thing here is that no results exist for mega VC firm analysis because the dataset does not record non-SBVF mega funds after 2016. Also, again, the coefficients for this analysis can be taken more lightly, as they are not significant at a confidence level of 90%.

This result is the manifestation of the “barriers to entry” idea in industrial organization literature. This force overpowers what agency theory would predict about VC firms’ tendency to invest in SBVF industries over non-technology industries.

Overall, my results confirm the channels and factors that affect low, middle, and mega size already-established and newly-established VC firms in terms of industry focus shift and changes in fund size. In not fully matching the predictions in my hypotheses, they also introduce and validate the additional factor of situation awareness, which increases with fund size and causes VC firms to realize that SBVF may perhaps simply be too hard to catch-up to or compete with, and thus situation awareness dampens or offsets any behavioral response that would drive VC firms to mimic SBVF’s strategy.

Many things may affect the significance of results in my analysis. One problem is that Masayoshi Son’s definition of “technology” is very broad. And his investment choices do not follow strict, careful, controlled process and/or due diligence. Another thing might be that VC practitioners were aware of plans for the Vision Fund before SoftBank posted the official disclosure in 2016. Although I cannot accurately test for this possibility, one option would be to run my main set of regressions with a cutoff of half to one year before the 2016 cutoff to check for significant results, which might indicate a likelihood of that scenario. Yet another thing is that one of the biggest investors in the Vision Fund is Saudi Arabia’s Public Investment Fund (PIF); this is addressed by doing intensive research on the PIF itself. Next, VC fundraising times vary widely by fund, and so there may be lags in VC firm responses to Vision Fund disclosure releases. However, the way I addressed this issue was to run regressions using funds with initial closes in the specific years of 2017 and 2018 after the cutoff and taking one year at a time. Furthermore, venture capital data is known to not have perfect coverage (Kaplan and Lerner (2016)); this lack of data may contribute to noise, unclear results, and lack of significance in analysis.

I summarize here my main supplemental robustness checks that may offer further interpretation of the aforementioned findings. Tables I, J, K, and L display the results of my first robustness check of re-running analysis but now with the cutoff brought one-year earlier to October 14, 2015. Tables M, N, O, and P display the results of my second robustness check of re-running analysis but now with the cutoff brought one-year later to October 14, 2017. Of these supplemental analyses, it is apparent that many channels of robustness checks have a combination of both significant and nonsignificant coefficients, some of which agree with my hypotheses for the actual cutoff of October 14, 2016 and some of which do not. Due to the fact that a lot of the results for the analysis for the actual cutoff of October 14, 2016 itself are not significant, that the VC industry is very volatile and full of noise due to variation in many steps along the fund raising and investment processes, and that many shocks affect the VC industry every year from policy changes to public market swings, these robustness checks cannot say much either for or against the strength of the results for my analysis for the October 14, 2016 cutoff.

VI. CONCLUSION AND FURTHER RESEARCH

The private equity landscape is seeing ever increasing valuations and the rise of mega funds, and SoftBank Vision Fund may be a major factor driving these recent changes in the industry. This paper looks at how VC firms in different size categories react to the current heavily SBVF-influenced venture capital environment. VC firms have multiple options at their disposal in their reactions, but the options of interest in this paper are (1) changes in fund size, as well as (2) the potential shift away from industries saturated with SBVF money toward those with less. In other words, I investigate two questions about industry shift and fund size changes. For investigating industry shift, I seek to answer the following: after the VC industry became aware of the large presence and size of Softbank's Vision Fund, will new funds raised by VC firms begin to shift their industry focus away from or toward technology and other industries in which Softbank heavily invests? For looking at fund size changes, the question to answer is: will these funds also begin to deviate from the size trends of the pre-Vision Fund period?

Again, my results confirm potential factors that attract or deter VC firms from following SBVF in its strategy of raising huge funds and investing in technology and other industries in which SBVF is interested. Factors that attract VC firms to follow SBVF in its strategy include behavioral factors, beliefs formed by reputation signaling or certification, and herding. Factors that deter VC firms from following SBVF in its strategy include agency costs, long-term reputation consequences, operational costs, and status quo bias. Another significant factor that can vary with fund size is situation awareness, which also can offset behavioral responses toward mimicking SBVF's strategy. The interpretation of my results depends on my claim that in the environment of interest in this paper, entrepreneurs will weight money over non-monetary support in deciding which VC firms' support to accept.

This paper thus takes these first steps toward learning about the extent and channels through which shocks like SBVF may influence and disrupt the U.S. VC industry. The findings here also have major implications for real costs or inefficiencies that occur due to the end of a cycle driven by factors like SBVF, as well as implications for the change in innovation levels in the United States which implies real effects on economic growth.

Many avenues for further research stem from this paper. To further build on this research question in the future, I would analyze limited partners' investment behavior in terms of the funds they choose to invest in in the Vision Fund's wake. Further research may be on how the changing VC landscape affects the health and characteristics of technology or non-technology industries themselves. As described in this paper, agency costs may arise in environments that experience shocks; the measurement of these agency costs would be of interest for further research or a deeper dive. Finally, more research can and should also be done on the most appropriate responses to shifts in VC landscape that occur due to disruptors such as the Vision Fund.

VII. FIGURES AND TABLES

Table 1: Hypotheses for Analyses

Analysis	Positive coefficient interpretation for treatment group funds due to SoftBank	Hypothesis		
		Low	Mid	Mega
Already-established fund size	Increase in fund size	-, 0	-, 0	+
Already-established industry shift	Increase in SoftBank industry deal %	N/A	N/A	0,+
Newly-established fund size	Increase in fund size	+	+	+
Newly-established industry shift	Increase in SoftBank industry deal %	-	-	-

The hypotheses are separated by size category under the "Hypothesis" heading in the right-hand column of the table. "N/A" refers to having hypotheses that are not clear due to opposing views. "0" refers to no significant change, or a 0 coefficient in regression analyses. "+" refers to a positive significant coefficient in regression analyses. "-" refers to a negative significant coefficient in regression analyses.

Table 2: Summary Statistics on Already-Established VC Firm Dataset

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
Percentage of deals made in SoftBank industry in a fund	354	0.810	0.343	0	1
Dummy for Fund Classification as SoftBank industry	354	0.825	0.381	0	1
Dummy for Pre-/Post-Cutoff	354	0.463	0.499	0	1
Quarterly Inflow into VC	354	10,298	3,961	2,186	21,022
VC Firm Experience from 2011 to Cutoff	354	1.932	1.304	1	8

This table provides key summary statistics of main variables of the dataset of already-established VC firms used in analysis. The first variable is the average percentage of deals in a fund that is made with portfolio companies that are in a SoftBank industry. The second variable is a dummy that classifies VC funds as 1 if a majority of their portfolio company deals are made in a SoftBank industry, or an industry that SoftBank invests in, and 0 otherwise. The third variable is a dummy for pre-/post-cutoff that classifies whether funds had their initial close before or after cutoff, with a value of 1 if funds had initial close after the cutoff. The fourth variable is quarterly inflow into venture capital, or the quarterly aggregate capital raised in the U.S in millions USD. The last variable is number of funds raised by a firm in the pre-cutoff period since 2011.

Table 3: Summary Statistics on Newly-Established VC Firm Dataset

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
Percentage of deals made in SoftBank industry in a fund	812	0.811	0.343	0	1
Dummy for Fund Classification as SoftBank industry	812	0.829	0.377	0	1
Dummy for Pre-/Post-Cutoff	812	0.336	0.473	0	1

This table provides key summary statistics of main variables of the dataset of already-established VC firms used in analysis. The first variable is the average percentage of deals in a fund that is made with portfolio companies that are in a SoftBank industry. The second variable is a dummy that classifies VC funds as 1 if a majority of their portfolio company deals are made in a SoftBank industry, or an industry that SoftBank invests in, and 0 otherwise. The third variable is a dummy for pre-/post-cutoff that classifies whether funds had their initial close before or after cutoff, with a value of 1 if funds had initial close after the cutoff.

Table 4A: Tabulation of Size Category for Already-Established Firm Dataset

Size Category	Count	Mean of Industry Classification Dummy
Low	123	.927
Middle	174	.759
Mega	57	.807

This table provides detailed and broken down summary statistics for main variables of interest used in analysis with the already-established VC firm dataset. This table breaks down the number of VC funds by each size channel category and gives the mean of the industry classification dummy, which equals 1 when investment focus is in technology, 0 when investment focus is not technology. The mean of the industry classification dummy can be understood as the percentage of funds within a size channel category that is classified as investing in majority SoftBank industry portfolio companies.

Table 4B: Tabulation of Fund Year for Already-Established Firm Dataset

Fund Initial Closing Year	Count	Mean of Industry Classification Dummy
2011	15	.933
2012	27	.963
2013	20	.8
2014	49	.837
2015	39	.795
2016	52	.731
2017	51	.843
2018	62	.903
2019	39	.692

This table provides detailed and broken down summary statistics for main variables of interest used in analysis with the already-established VC firm dataset. This table breaks down the number of VC funds by year of a fund's initial closing and gives the mean of the industry classification dummy, which equals 1 when investment focus is in technology, 0 when investment focus is not technology. The mean of the industry classification dummy can be understood as the percentage of funds within a year that is classified as investing in majority SoftBank industry portfolio companies.

Table 4C: Tabulation of Size Category & Fund Year for Already-Established Firm Dataset

Size Category	Fund Initial Closing Year								
	2011	2012	2013	2014	2015	2016	2017	2018	2019
Count for Low	4	9	8	20	14	13	21	23	11
Ind. Dummy Mean - Low	1	1	1	.95	.857	.923	.952	.913	.818
Count for Middle	8	12	9	21	19	29	25	28	23
Ind. Dummy Mean - Middle	.875	.917	.778	.667	.789	.621	.84	.893	.609
Count for Mega	3	6	3	8	6	10	5	11	5
Ind. Dummy Mean - Mega	1	1	.333	1	.667	.8	.4	.909	.8

This table provides detailed and broken down summary statistics for main variables of interest used in analysis with the already-established VC firm dataset. This table breaks down the number of VC funds by both size channel category and year of a fund's initial closing and gives the mean of the industry classification dummy, which equals 1 when investment focus is in technology, 0 when investment focus is not technology. The mean of the industry classification dummy can be understood as the percentage of funds within a size channel category and year that is classified as investing in majority SoftBank industry portfolio companies.

Table 5A: Tabulation of Size Category for Newly-Established Firm Dataset

Size Category	Count	Mean of Industry Classification Dummy
Low	472	.847
Middle	311	.807
Mega	29	.759

This table provides detailed and broken down summary statistics for main variables of interest used in analysis with the newly-established VC firm dataset. This table breaks down the number of VC funds by each size channel category and gives the mean of the industry classification dummy, which equals 1 when investment focus is in technology, 0 when investment focus is not technology. The mean of the industry classification dummy can be understood as the percentage of funds within a size channel category that is classified as investing in majority SoftBank industry portfolio companies.

Table 5B: Tabulation of Fund Year for Newly-Established Firm Dataset

Fund Initial Closing Year	Count	Mean of Industry Classification Dummy
2011	85	.8
2012	78	.872
2013	64	.812
2014	119	.782
2015	100	.89
2016	109	.817
2017	85	.788
2018	121	.851
2019	51	.863

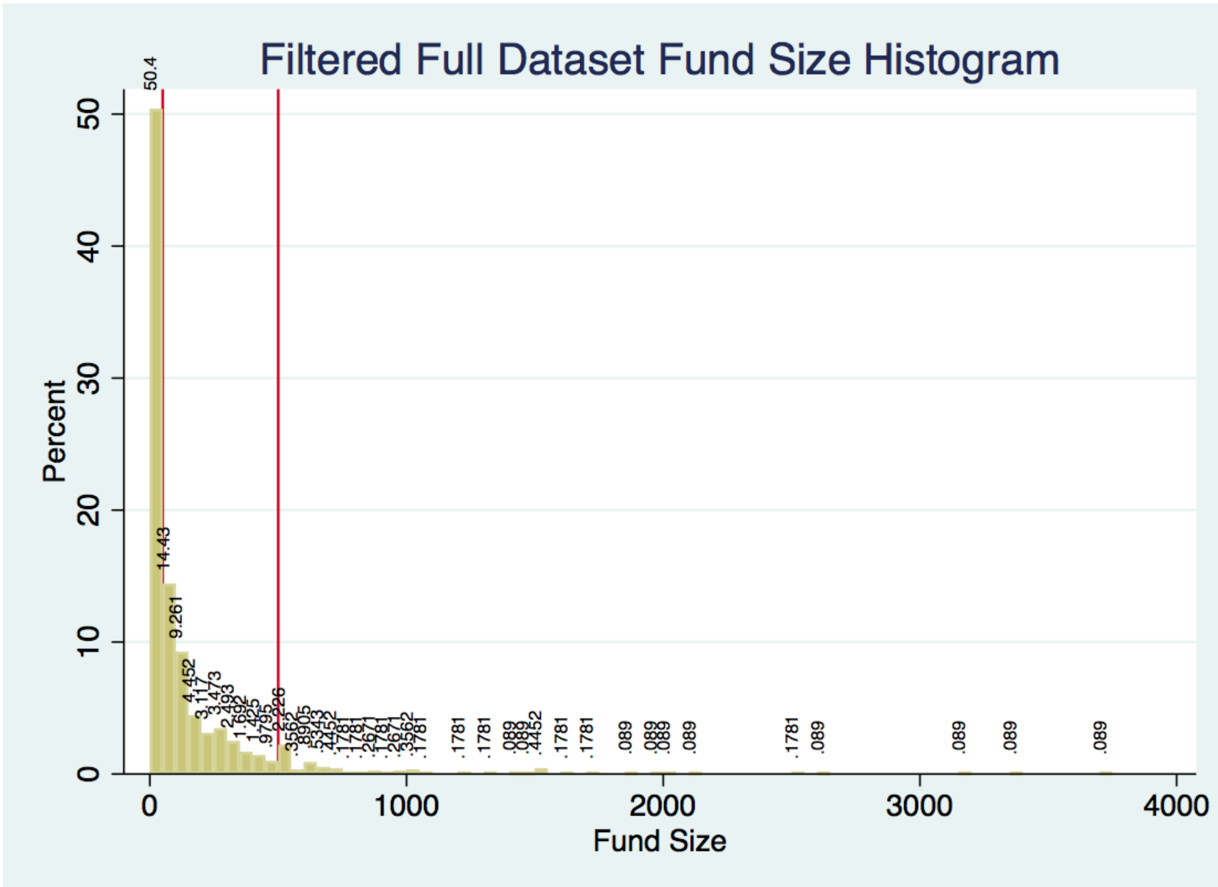
This table provides detailed and broken down summary statistics for main variables of interest used in analysis with the newly-established VC firm dataset. This table breaks down the number of VC funds by year of a fund's initial closing and gives the mean of the industry classification dummy, which equals 1 when investment focus is in technology, 0 when investment focus is not technology. The mean of the industry classification dummy can be understood as the percentage of funds within a year that is classified as investing in majority SoftBank industry portfolio companies.

Table 5C: Tabulation of Size Category & Fund Year for Already-Established Firm Dataset

Size Category	Fund Initial Closing Year								
	2011	2012	2013	2014	2015	2016	2017	2018	2019
Count for Low	46	42	38	73	52	62	60	69	30
Ind. Dummy Mean - Low	.783	.881	.895	.836	.923	.823	.817	.841	.867
Count for Middle	32	30	22	45	44	42	24	51	21
Ind. Dummy Mean - Middle	.812	.833	.727	.711	.886	.81	.708	.863	.857
Count for Mega	7	6	4	1	4	5	1	1	
Ind. Dummy Mean - Mega	.857	1	.5	0	.5	.8	1	1	

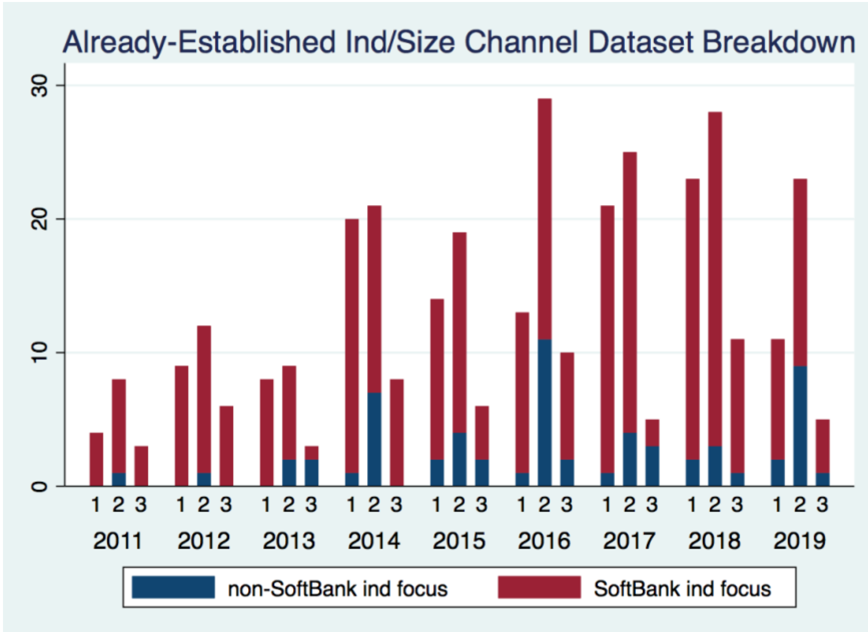
This table provides detailed and broken down summary statistics for main variables of interest used in analysis with the newly-established VC firm dataset. This table breaks down the number of VC funds by both size channel category and year of a fund's initial closing and gives the mean of the industry classification dummy, which equals 1 when investment focus is in technology, 0 when investment focus is not technology. The mean of the industry classification dummy can be understood as the percentage of funds within a size channel category and year that is classified as investing in majority SoftBank industry portfolio companies.

Figure 1: Overall Picture of Full Cleaned Dataset on Fund Size



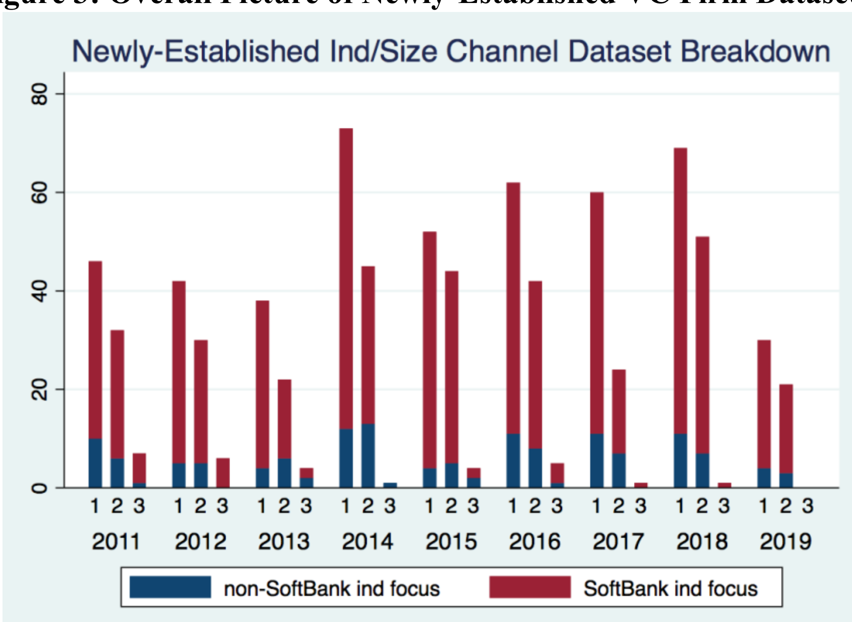
This figure provides the distribution of fund sizes in millions of USD within the full cleaned dataset (before splitting into already-established and newly-established datasets for analysis). Vertical labels represent the percentage of funds in each bin of fund size 50 million USD. Red vertical lines represent, from left to right, the cutoff between lower and middle sized funds, and the cutoff between middle sized and mega funds, respectively. The lower sized funds make up the bottom 50% of the dataset, and the mega sized funds make up the top 10% of the dataset.

Figure 2: Overall Picture of Already-Established VC Firm Dataset



This figure provides the number of funds within the already-established dataset for analysis. In this stacked bar chart, red bars represent the number of VC funds in a given year and size channel that have invested in majority SoftBank industry portfolio companies. Blue bars represent the number of VC funds invested in majority non-SoftBank industry portfolio companies. The 1, 2, and 3 labels carry the number of VC funds raised by firms categorized into "low," "middle," and "mega," size channels, respectively.

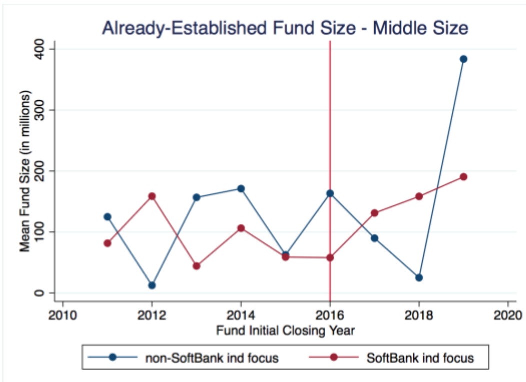
Figure 3: Overall Picture of Newly-Established VC Firm Dataset



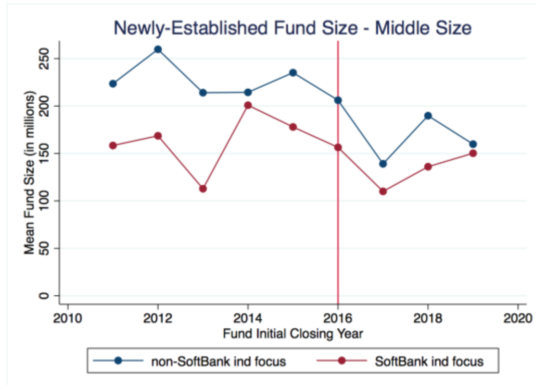
This figure provides the number of funds within the newly-established dataset for analysis. In this stacked bar chart, red bars represent the number of VC funds in a given year and size channel that have invested in majority SoftBank industry portfolio companies. Blue bars represent the number of VC funds invested in majority non-SoftBank industry portfolio companies. The 1, 2, and 3 labels carry the number of VC funds raised by firms categorized into "low," "middle," and "mega," size channels, respectively.

Figure 4: Representative Event Study Graphs for Middle Size Category Analysis

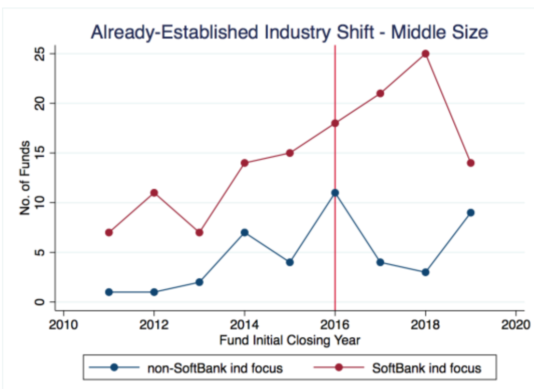
A



B



C



D

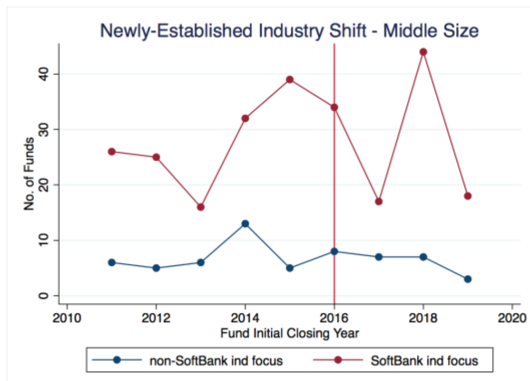


Figure 4A features event study graphs for already established VC firms, separate for each size channel category for fund size. The y-axis refers to the mean fund size in millions of U.S. dollars for each year, and the x-axis refers to the year of a fund's initial closing. The funds are classified as either SoftBank industry focused or non-SoftBank industry focused based on which category constitutes the majority of investments on average for all of a VC firm's pre-cutoff funds. Red lines represent data for the treatment group, blue lines represent data for the control group.

Figure 4B features event study graphs for newly established VC firms, separate for each size channel category for fund size. The funds are classified as either SoftBank industry focused or non-SoftBank industry focused based on which category constitutes the majority of investments for each fund.

Figure 4C features the middle size event study graphs for already established VC firms, for industry shift. The y-axis refers to the number of funds for each year, and the x-axis refers to the year of a fund's initial closing. The funds are classified as either SoftBank industry focused or non-SoftBank industry focused based on which category constitutes the majority of investments for each fund.

Figure 4D features event study graphs for newly established VC firms, separate for each size channel category for industry shift. The funds are classified as either SoftBank industry focused or non-SoftBank industry focused based on which category constitutes the majority of investments for each fund.

ALREADY-ESTABLISHED VC FIRM FUND SIZE ANALYSIS

Table 6: DiD for Fund Size for Already-Established Firms (Main Results)

VARIABLES	(1) Low Size Channel All Controls	(2) Low Size Channel 2017 All Controls	(3) Low Size Channel 2018 All Controls	(4) Middle Size Channel All Controls	(5) Middle Size Channel 2017 All Controls	(6) Middle Size Channel 2018 All Controls	(7) Mega Size Channel All Controls	(8) Mega Size Channel 2017 All Controls	(9) Mega Size Channel 2018 All Controls
TREAT	-13.53	47.27***	-30.02***	-61.68	-143.9	-26.07	290.6	2,628	625.4
	(16.11)	(5.054)	(6.109)	(41.34)	(131.4)	(43.68)	(428.9)	(2,789)	(448.4)
TREAT*POST Interaction	27.79	0.801	3.285	17.82	10.90	-22.13	453.7	-1,288	-693.6
	(23.71)	(5.237)	(8.837)	(73.70)	(130.5)	(54.71)	(520.2)	(5,161)	(749.2)
Quarterly VC Inflow	0.00240*	0.00244*	0.00104	0.00685	0.00803	0.00182	0.0105	0.0393	0.0257
	(0.00118)	(0.00124)	(0.00152)	(0.0109)	(0.0306)	(0.00666)	(0.0504)	(0.454)	(0.0862)
VC Firm Experience	3.128	40.81***	-2.978	4.694	22.95	73.47***	16.73	-855.7	305.5***
	(5.346)	(4.299)	(7.942)	(10.29)	(26.43)	(14.58)	(101.7)	(968.3)	(71.37)
Constant	8.219	-75.33***	80.04*	132.9***	528.9***	79.53	559.5	264.3	337.3
	(18.09)	(12.14)	(35.74)	(38.98)	(117.4)	(55.97)	(362.5)	(2,468)	(394.3)
Observations	123	49	45	174	76	77	57	17	31
R-squared	0.245	0.641	0.286	0.095	0.097	0.299	0.142	0.516	0.284
Fund Stage Ctrl	YES	YES	YES	YES	YES	YES	YES	YES	YES
Quarterly Inflow Ctrl	YES	YES	YES	YES	YES	YES	YES	YES	YES
Experience Ctrl	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

This table provides the results of regressions for already-established firms for the dependent variable of fund size on each size channel category (low, middle, mega) of VC funds. For each size channel category, two more regressions are run on only the funds with initial closing in 2017 and then only the funds with initial closing in 2018. All controls (quarterly inflow/capital raised, VC firm experience, fund stage) and year fixed effects are used in these regression results. Clustered robust standard errors by year.

NEWLY-ESTABLISHED VC FIRM FUND SIZE ANALYSIS

Table 7: Analysis for Fund Size for Newly-Established Firms

VARIABLES	(1) Overall Yearly All Control	(2) Overall Yearly No Control	(3) Lower Yearly All Control	(4) Lower Yearly No Control	(5) Middle Yearly All Control	(6) Middle Yearly No Control	(7) Mega Yearly All Control	(8) Mega Yearly No Control
TREAT	-40.24	-40.24	0.818	0.818	-63.02***	-63.02***	385.7**	305.2
	(26.25)	(25.41)	(2.043)	(2.117)	(15.33)	(14.84)	(120.8)	(235.9)
POST	-83.59***	-86.10***	1.308	-0.810	-72.40***	-62.63***	-111.5	259.5
	(19.91)	(18.90)	(3.057)	(3.558)	(18.91)	(15.93)	(286.3)	(358.5)
TREAT*POST Interaction	36.15	36.15	4.549	4.549	32.22	32.22		
	(28.33)	(27.10)	(3.415)	(3.678)	(21.66)	(22.92)		
Yearly Inflow into VC	-0.199		-0.168		0.776		14.29*	
	(1.112)		(0.117)		(0.756)		(6.462)	
Constant	165.8***	160.1***	19.80***	14.97***	203.2***	225.5***	241.5	550.3***
	(42.69)	(18.54)	(4.797)	(2.087)	(21.32)	(8.242)	(166.7)	(146.6)
Observations	18	18	18	18	18	18	12	14
R-squared	0.557	0.556	0.352	0.222	0.748	0.726	0.609	0.234
Yearly Inflow Ctrl	YES	NO	YES	NO	YES	NO	YES	NO

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table provides the results of regressions for newly-established firms for the dependent variable of fund size on each size channel category (low, middle, mega) of VC funds as well as on the overall full sample. This table displays results of regressions both with the control of yearly inflows into VC as well as without.

ALREADY-ESTABLISHED VC FIRM INDUSTRY SHIFT ANALYSIS

Table 8: DiD for Industry Shift for Already-Established Firms (Main Results)

VARIABLES	(1) Low Size Channel All Controls	(2) Low Size Channel 2017 All Controls	(3) Low Size Channel 2018 All Controls	(4) Middle Size Channel All Controls	(5) Middle Size Channel 2017 All Controls	(6) Middle Size Channel 2018 All Controls	(7) Mega Size Channel All Controls	(8) Mega Size Channel 2017 All Controls	(9) Mega Size Channel 2018 All Controls
TREATMENT	-0.0346	-0.435***	-0.0501***	0.0586	0.197*	0.159	-0.156**	-0.277***	-0.0580*
	(0.0957)	(0.0182)	(0.0117)	(0.0402)	(0.0897)	(0.100)	(0.0481)	(0.0236)	(0.0295)
Quarterly VC Inflow	3.70e-06	7.02e-06	1.47e-05***	5.47e-06	7.33e-06	-5.24e-08	-5.48e-06	1.61e-06	-1.62e-06
	(6.19e-06)	(1.28e-05)	(3.22e-06)	(4.52e-06)	(6.40e-06)	(8.14e-06)	(4.62e-06)	(7.20e-06)	(1.33e-06)
VC Firm Experience	-0.00528	-0.00462	0.00482	0.0361*	0.0408*	-0.0165	0.0397***	-0.297***	0.0248*
	(0.00884)	(0.0200)	(0.0201)	(0.0174)	(0.0178)	(0.0241)	(0.0106)	(0.0195)	(0.0121)
Constant	-0.00994	0.410***	0.0342	-0.129	-0.252**	-0.120	0.0223	0.572***	-0.0970***
	(0.115)	(0.119)	(0.0343)	(0.0793)	(0.107)	(0.166)	(0.0639)	(0.0508)	(0.0162)
Observations	123	49	45	174	76	77	57	17	31
R-squared	0.082	0.311	0.315	0.056	0.192	0.143	0.405	0.991	0.467
Fund Stage Ctrl	YES	YES	YES	YES	YES	YES	YES	YES	YES
Quarterly Inflow Ctrl	YES	YES	YES	YES	YES	YES	YES	YES	YES
Experience Ctrl	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table provides the results of regressions for already-established firms for the dependent variable of industry shift on each size channel category (low, middle, mega) of VC funds. For each size channel category, two more regressions are run on only the funds with initial closing in 2017 and then only the funds with initial closing in 2018. All controls (quarterly inflow/capital raised, VC firm experience, fund stage) and year fixed effects are used in these regression results. Clustered robust standard errors by year.

NEWLY-ESTABLISHED VC FIRM INDUSTRY SHIFT ANALYSIS

Table 9: Analysis for Industry Shift for Newly-Established Firms

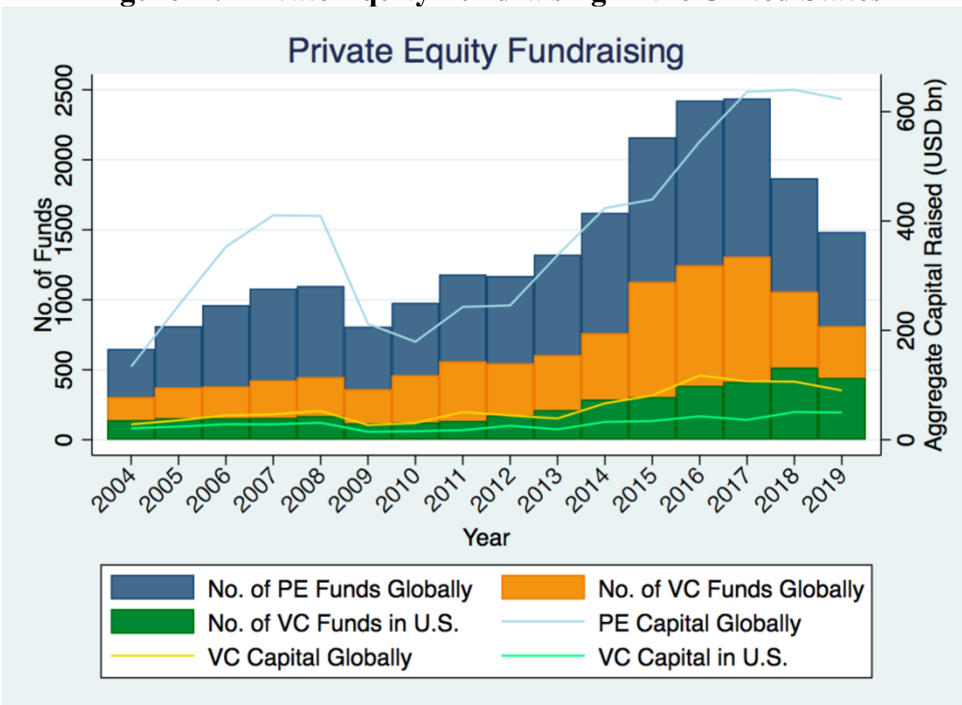
VARIABLES	(1) Overall Yearly All Control	(2) Overall Yearly No Control	(3) Lower All Control	(4) Lower No Control	(5) Middle All Control	(6) Middle No Control	(7) Mega All Control	(8) Mega No Control
TREAT	60.50***	60.50***	36.83***	36.83***	21.50***	21.50***	2.566**	2.600**
	(5.893)	(7.376)	(4.008)	(4.762)	(3.098)	(3.656)	(0.974)	(0.958)
POST	-13.80	-1.667	-5.278	1	-7.752*	-1.500	-2.649**	-3**
	(7.819)	(4.296)	(4.133)	(2.673)	(4.158)	(1.788)	(0.850)	(0.924)
TREAT*POST Interaction	-3.500	-3.500	-1.167	-1.167	-0.833	-0.833		
	(15.97)	(17.85)	(9.777)	(10.25)	(7.757)	(9.047)		
Yearly Inflow into VC	0.965**		0.499**		0.497**		-0.0251	
	(0.341)		(0.176)		(0.195)		(0.0384)	
Constant	-11.70	16***	-6.661	7.667***	-7.102	7.167***	2.136	1.400***
	(10.38)	(2.632)	(5.767)	(1.574)	(5.511)	(1.293)	(1.187)	(0.253)
Observations	18	18	18	18	18	18	12	12
R-squared	0.879	0.825	0.870	0.831	0.800	0.705	0.574	0.558
Yearly Inflow Ctrl	YES	NO	YES	NO	YES	NO	YES	NO

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

This table provides the results of regressions for newly-established firms for the dependent variable of industry shift on each size channel category (low, middle, mega) of VC funds as well as on the overall full sample. This table displays results of regressions both with the control of yearly inflows into VC as well as without.

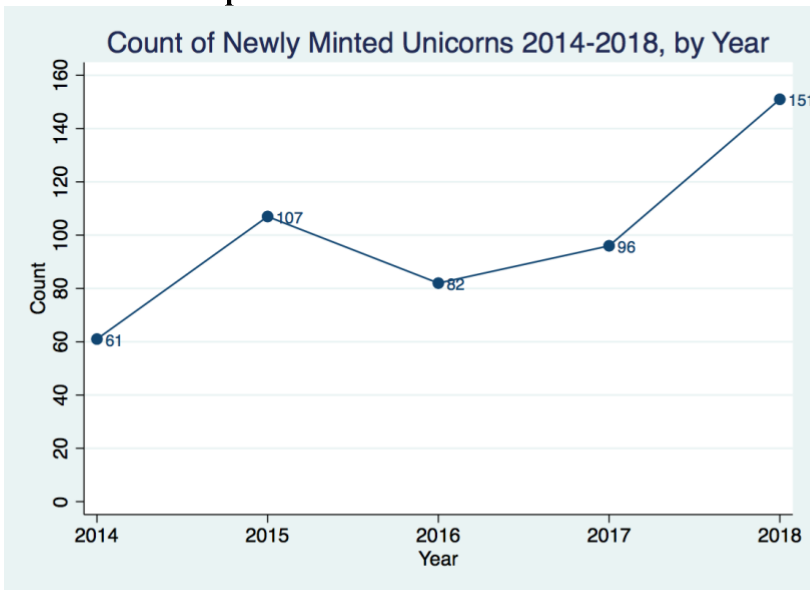
VIII. APPENDIX

Figure A: Private Equity Fundraising in the United States



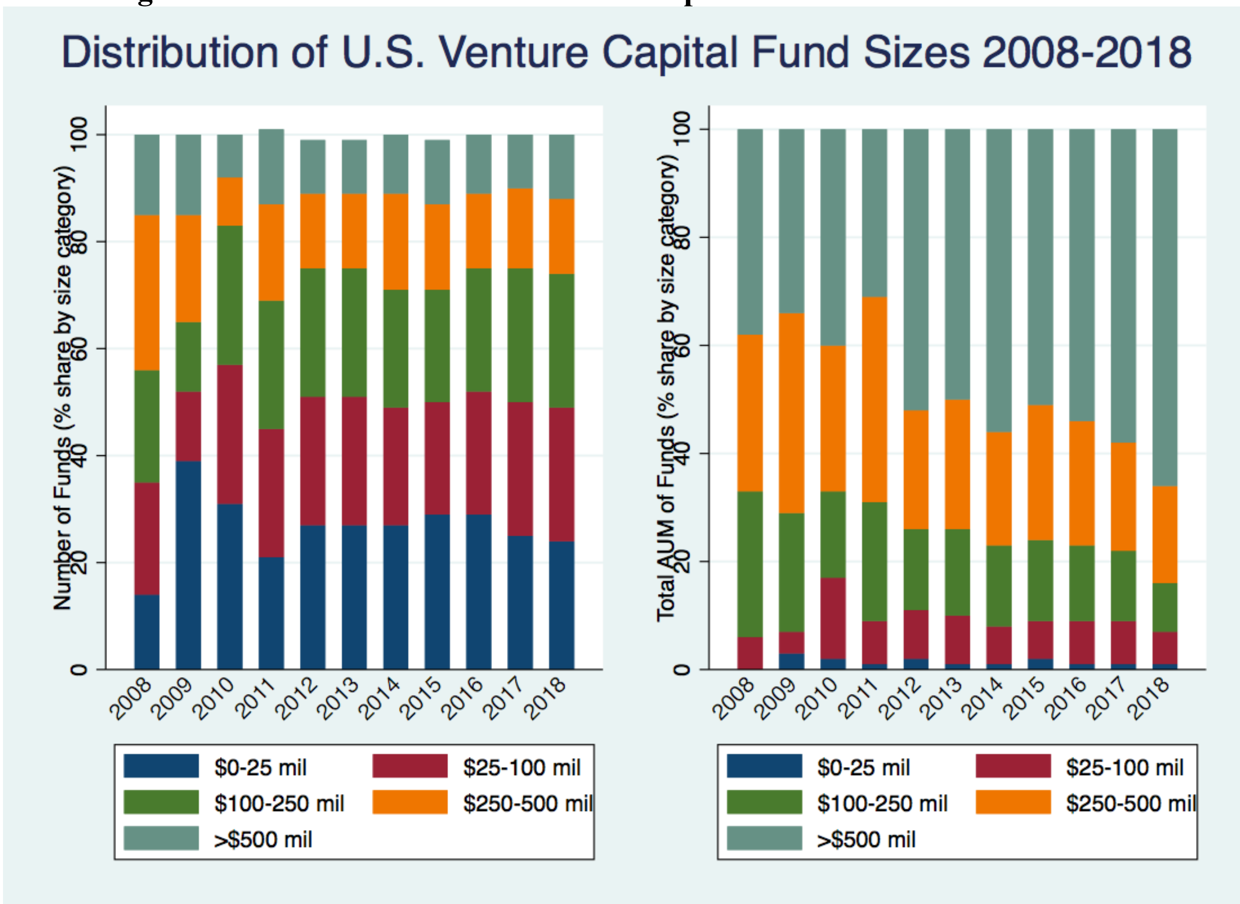
This figure shows, in an overlaid bar chart, the global number and aggregate capital raised of private equity funds and venture capital funds as well as the number of and aggregate capital raised of venture capital funds in the United States. Source of data: Preqin.

Figure B: Number of Companies that Reach Unicorn Status 2014-2018, by Year



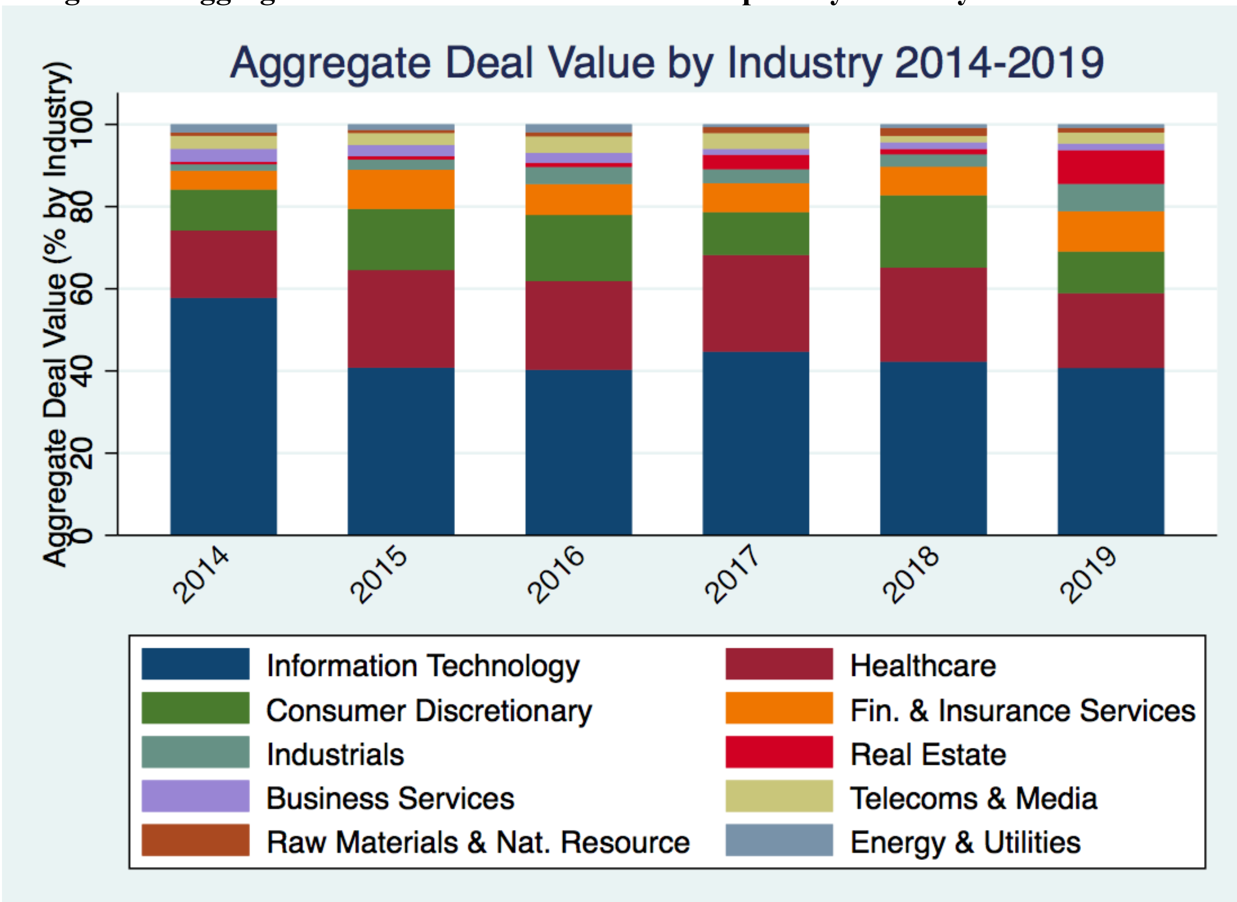
This figure shows the number of companies that reach unicorn status in a given year in the year range 2014-2018, where unicorn status is defined by a company reaching a 1 billion dollar post-money valuation. Source: TechCrunch, 2019.

Figure C: Distribution of U.S. Venture Capital Fund Sizes 2008-2018



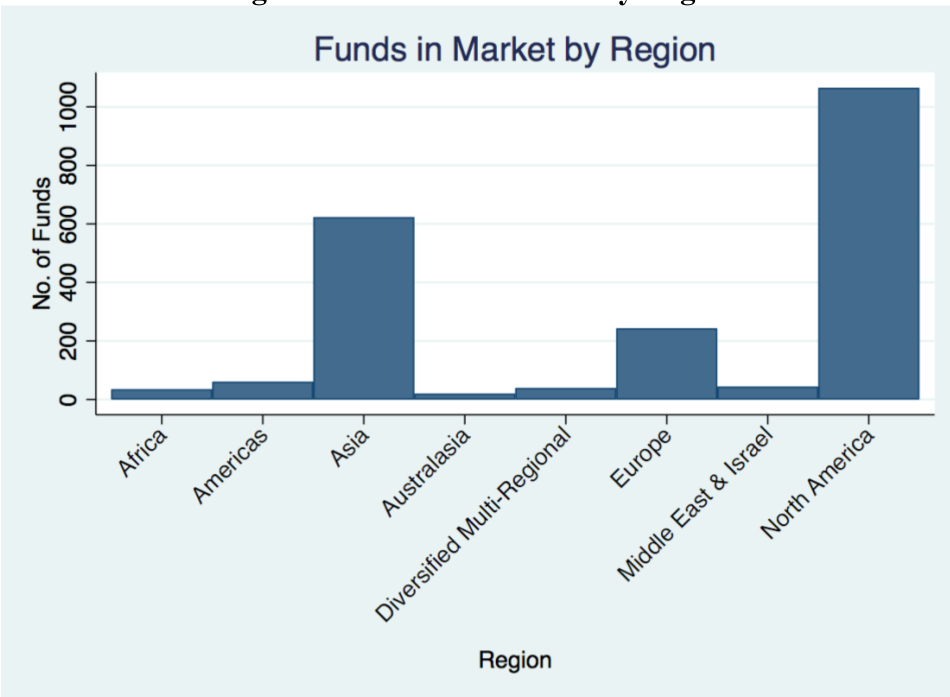
This figure shows the annual distribution of U.S. venture capital funds, in a stacked bar chart, in terms of (1) the number of funds in each of 5 size categories and (2) the total AUM of funds in each of 5 size categories. These 5 size categories are determined by the funds' AUM in USD millions. The table shows that the number of venture capital funds by size category has generally stayed constant over the past 10 years, but that there has been a significant increase in fundraising especially in the largest mega funds with AUM over 500 million dollars. Source: TopTal and Crunchbase, 2019.

Figure D: Aggregate Deal Value in U.S. Venture Capital by Industry 2014-2019



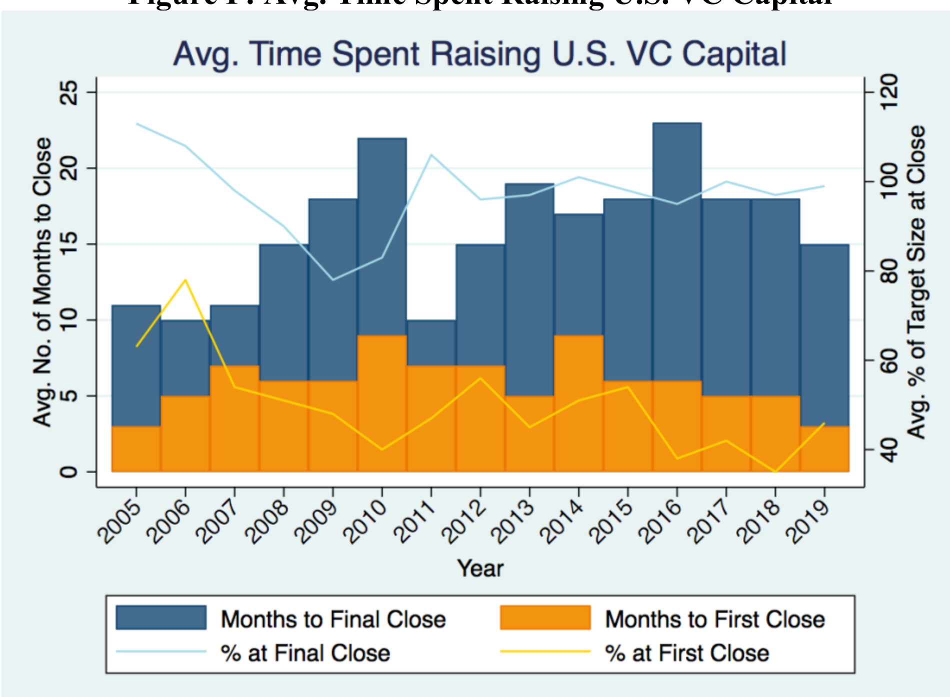
This figure shows the aggregate deal value for U.S. venture capital by industry as a share/percentage of the total. This stacked bar chart shows data for each of the years 2014-2018. Source: Preqin Pro.

Figure E: Funds in Market by Region



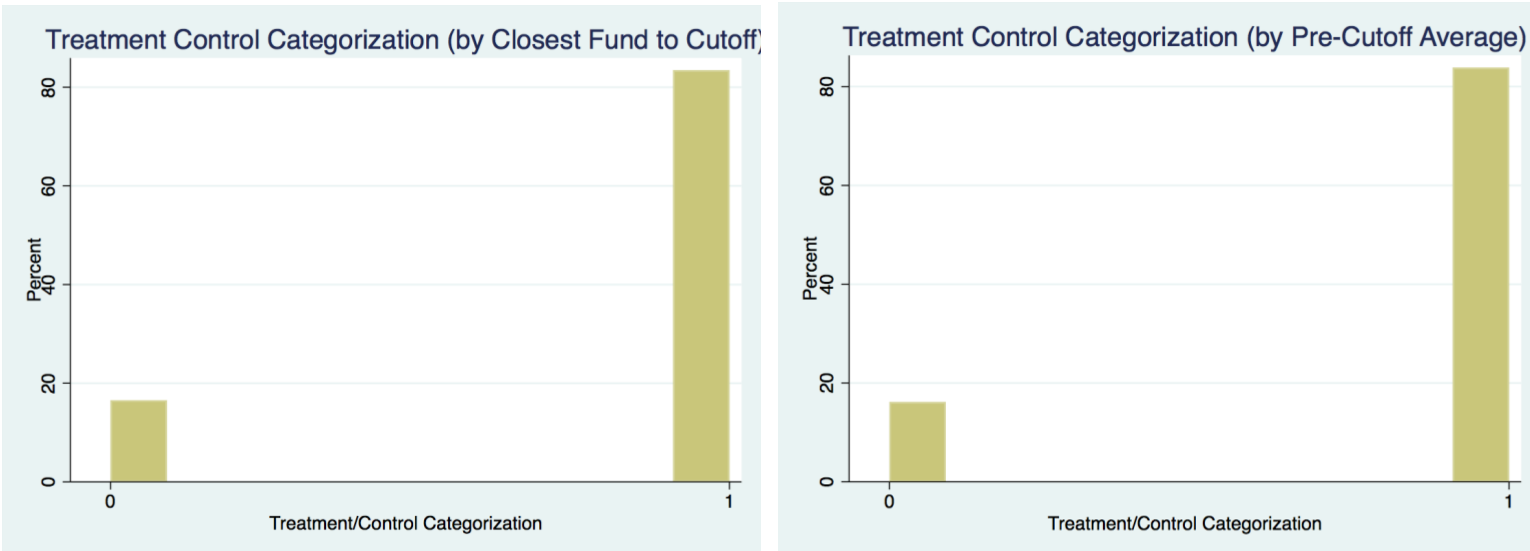
This figure shows the number of venture capital funds raised in each global region over time. Source of data: Preqin.

Figure F: Avg. Time Spent Raising U.S. VC Capital



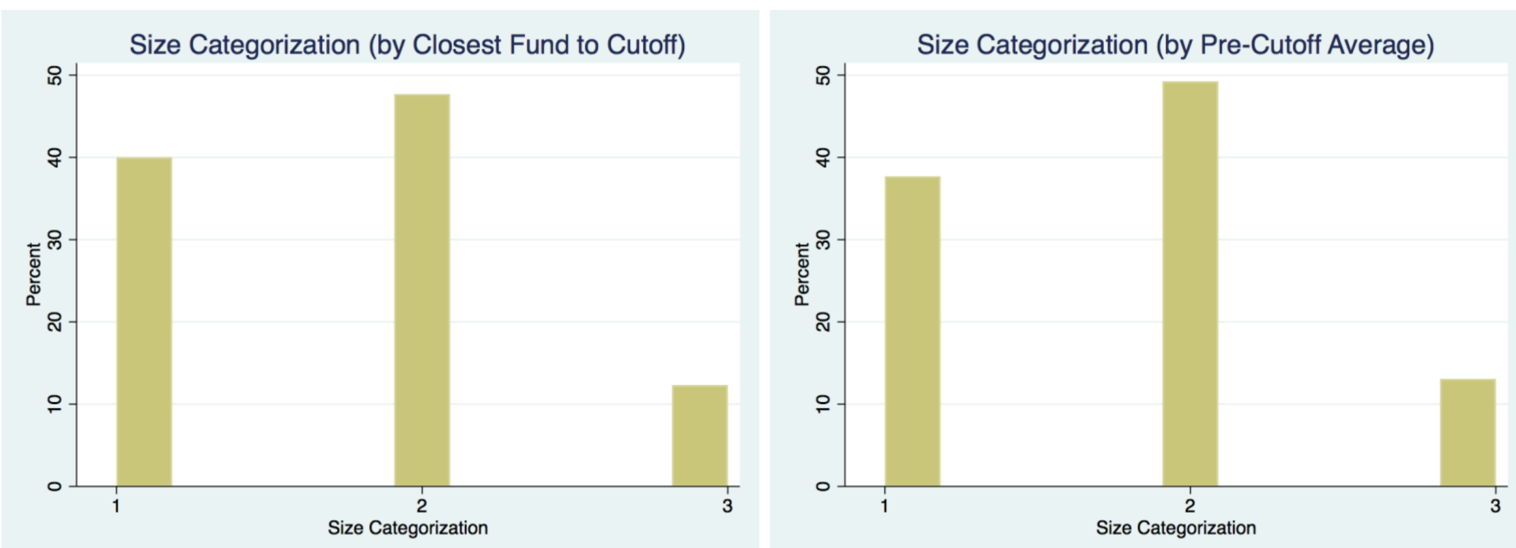
This figure shows, in an overlaid bar graph, the average time venture capital funds in the U.S. spend raising capital until first/initial close and until final close in the year range of 2005 to 2019 year to date. Source of data: Preqin.

Figure G: Comparison of Two Methodologies for Treatment Group Classification



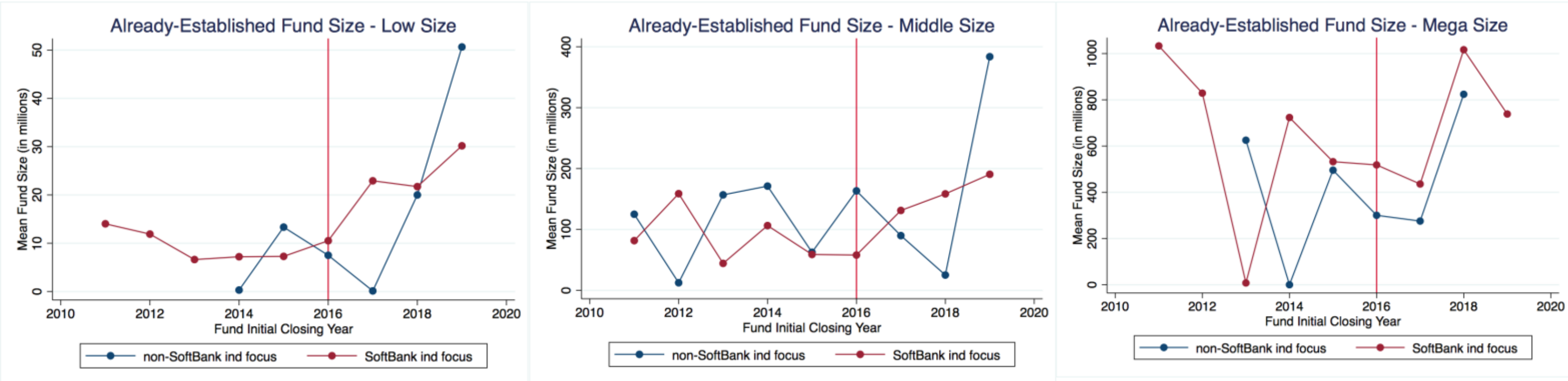
This figure serves as a robustness check to show that categorizing VC firms into treatment (investing in majority SoftBank industries) and control (investing in majority non-SoftBank industries) by taking the percentage of investments in SoftBank industry portfolio companies in the pre-cutoff fund closest to the cutoff is almost equivalent to taking the average of each fund's percentage of investments in SoftBank industry portfolio companies over the entire pre-cutoff period. In analysis, I use the latter method.

Figure H: Comparison of Two Methodologies for Size Channel Categorization



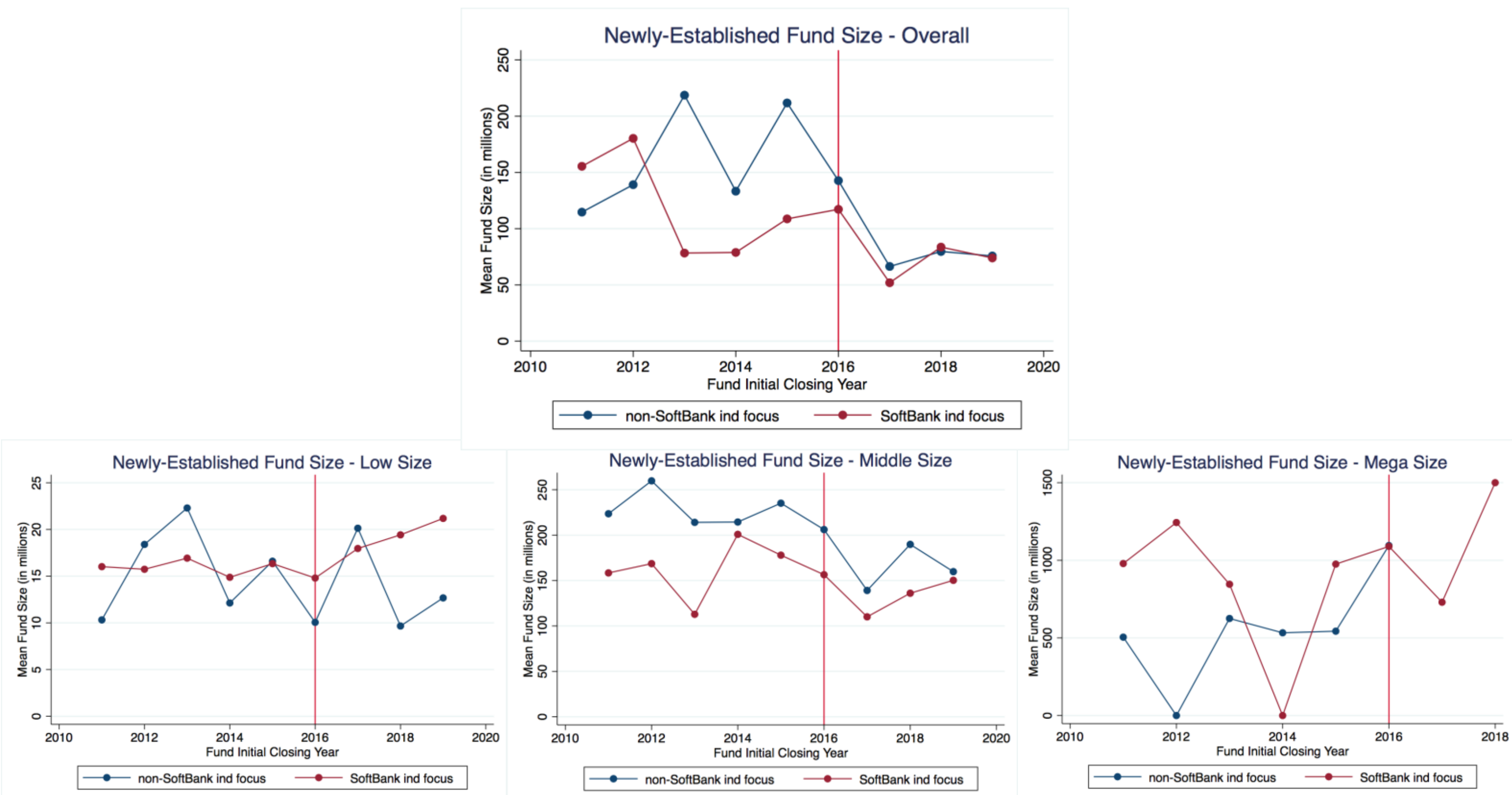
This figure serves as a robustness check to show that categorizing VC firms into size channel categories (low, middle, or mega) by taking the percentage of investments in SoftBank industry portfolio companies in the pre-cutoff fund closest to the cutoff is almost equivalent to taking the average of each fund's percentage of investments in SoftBank industry portfolio companies over the entire pre-cutoff period. In analysis, I use the latter method.

Figure I: Already-Established Fund Size Event Study Graph



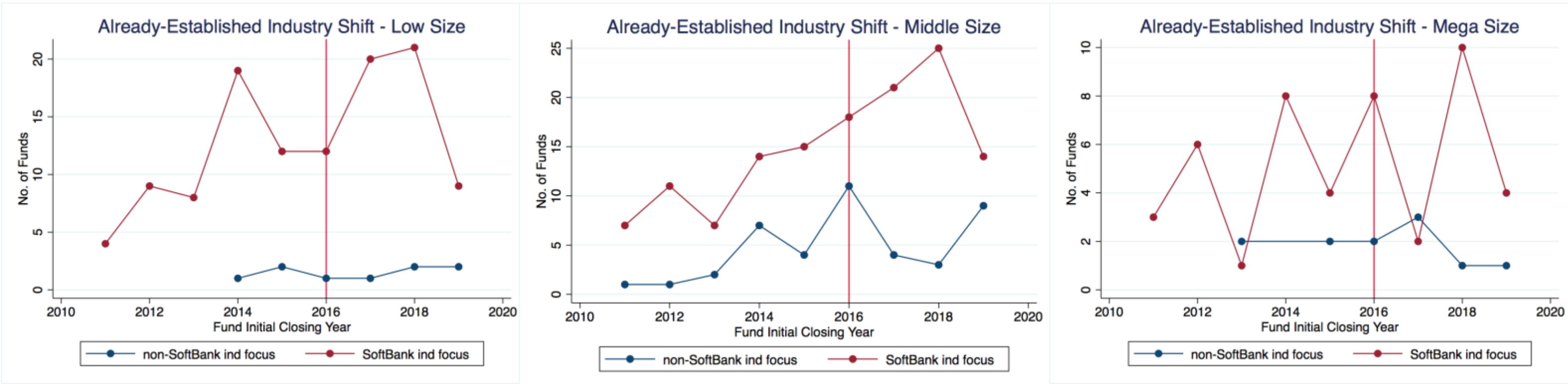
This figure features event study graphs for already established VC firms, separate for each size channel category for fund size. The y-axis refers to the mean fund size in millions of U.S. dollars for each year, and the x-axis refers to the year of a fund's initial closing. The funds are classified as either SoftBank industry focused or non-SoftBank industry focused based on which category constitutes the majority of investments on average for all of a VC firm's pre-cutoff funds. Red lines represent data for the treatment group, blue lines represent data for the control group.

Figure J: Newly-Established Fund Size Event Study Graph



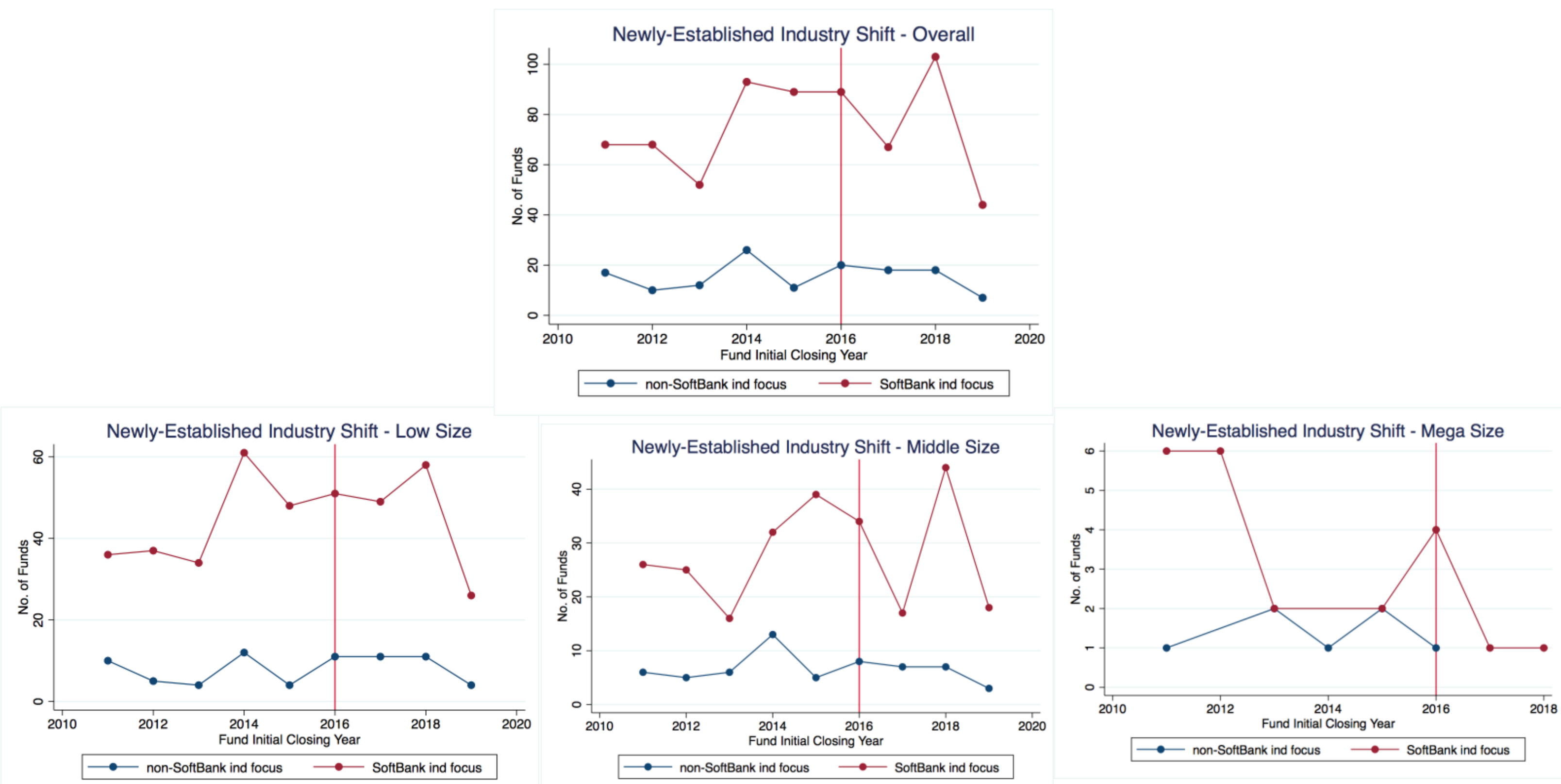
This figure features event study graphs for newly established VC firms, separate for each size channel category for fund size. The y-axis refers to the mean fund size in millions of U.S. dollars for each year, and the x-axis refers to the year of a fund's initial closing. The funds are classified as either SoftBank industry focused or non-SoftBank industry focused based on which category constitutes the majority of investments for each fund. Red lines represent data for the treatment group, blue lines represent data for the control group.

Figure K: Already-Established Industry Shift Event Study Graph



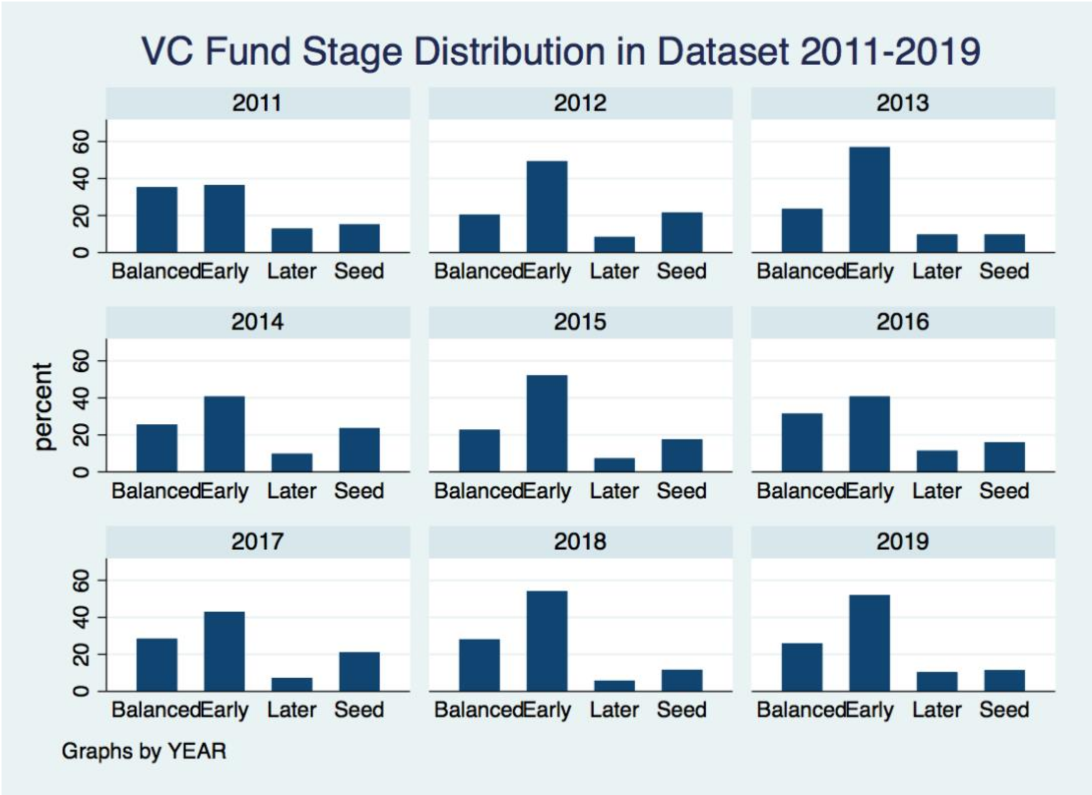
This figure features event study graphs for already established VC firms, separate for each size channel category for industry shift. The y-axis refers to the number of funds for each year, and the x-axis refers to the year of a fund's initial closing. The funds are classified as either SoftBank industry focused or non-SoftBank industry focused based on which category constitutes the majority of investments for each fund. Red lines represent data for the treatment group, blue lines represent data for the control group.

Figure L: Newly-Established Industry Shift Event Study Graph



This figure features event study graphs for newly established VC firms, separate for each size channel category for industry shift. The y-axis refers to the number of funds for each year, and the x-axis refers to the year of a fund's initial closing. The funds are classified as either SoftBank industry focused or non-SoftBank industry focused based on which category constitutes the majority of investments for each fund. Red lines represent data for the treatment group, blue lines represent data for the control group.

Figure M: VC Fund Stage Distribution in Full Cleaned Dataset 2011-2019



This figure shows that in the full cleaned dataset, the distribution of VC fund focusing on different portfolio company stages is similar for pre-treatment and post-treatment periods.

Table A: SoftBank Vision Fund Portfolio Companies (by Sector)

Sector	Company Name	Sector	Company Name
Consumer	Brandless	Health Tech	10x Genomics
	Coupang		Collective Health
	Fanatics		Guardant Health
	FirstCry		Ping An Good Doctor
	GetYourGuide		Ping An HealthKonnect
	Grofers		Relay Therapeutics
	Klook		Roivant
	Oyo		Vir
	Plenty	Real Estate	Clutter
	Tokopedia		Compass
Enterprise	Automation Anywhere		Katerra
	Cambridge Mobile Telematics		OpenDoor
	Cohesity		View
	Globality		WeWork
	Gympass	Transportation/Logistics	Alibaba Local Services
	MapBox		Auto1
	OSISoft		Delhivery
	Slack		DiDi
Fintech	C2FO		DoorDash
	Creditas		Fair
	Greensill		Flexport
	Kabbage		Full Truck Alliance
	OakNorth		Getaround
	OneConnect		GM Cruise
	Paytm		Grab
	Policy Bazaar		Guazi
	ZhongAn Insurance		Loggi
Frontier Tech	Arm		Nauto
	Brain Corp		Nuro
	CloudMinds		Ola
	Energy Vault		Rappi
	Fungible		REEF
	Improbable		Uber
	Light		Uber ATG
	Petuum		Zume
	Zymergen		

https://visionfund.com/portfolio

Table B: Thomson Portfolio Company Industry Classification	
Main Industry Class	**Industry SubGroup**
Information Technology	Internet Specific Computer Software Semiconductor/Electr Computer Hardware
Medical/Health/Life Science	Medical/Health Biotechnology
Non-High Technology	Consumer Related Industrial/Energy Financial Services Agr/Forestr/Fish Transportation Construction Business Services Manufacturing

Table C: DiD for Fund Size for Low-Size Already-Established Firms (Taking out Controls)

VARIABLES	(1) FS & QInflow	(2) FS & EXP	(3) QInflow & EXP	(4) FS	(5) QInflow	(6) EXP	(7) No Control
TREAT	-10.61	-16.96	-13.25	-14.97	-10.75	-16.55	-15.12
	(14.95)	(16.96)	(14.68)	(15.99)	(13.75)	(15.24)	(14.35)
TREAT*POST Interaction	25.97	30.86	28.22	29.58	26.77	31.36	30.49
	(22.06)	(22.38)	(23.80)	(20.87)	(22.38)	(22.23)	(20.82)
Quarterly VC Inflow	0.00223*		0.00249*		0.00232*		
	(0.00102)		(0.00123)		(0.00106)		
VC Firm Experience		1.918	2.828			1.433	
		(5.594)	(5.488)			(5.775)	
Constant	10.23	24.35	10.97	24.91	12.88	28.79*	29.15*
	(16.81)	(18.09)	(15.14)	(17.33)	(14.00)	(14.79)	(14.35)
Observations	123	123	123	123	123	123	123
R-squared	0.239	0.207	0.239	0.205	0.233	0.197	0.196
Fund Stage Ctrl	YES	YES	NO	YES	NO	NO	NO
Quarterly Inflow Ctrl	YES	NO	YES	NO	YES	NO	NO
Experience Ctrl	NO	YES	YES	NO	NO	YES	NO
Year FE	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table provides the results of regressions for already-established firms for the dependent variable of fund size on low size channel category VC funds. This table displays results of regressions in this size channel category that differ based on the combinations of controls (quarterly inflow/capital raised, VC firm experience, fund stage) included or left out to see if the inclusion or absence of certain controls affect analysis. Clustered robust standard errors by year.

Table D: DiD for Fund Size for Middle-Size Already-Established Firms (Taking out Controls)

VARIABLES	(1) FS & QInflow	(2) FS & EXP	(3) QInflow & EXP	(4) FS	(5) QInflow	(6) EXP	(7) No Control
TREAT	-59.55	-55.85	-59.13	-54.86	-59.66	-53.60	-54.81
	(38.91)	(39.06)	(34.81)	(37.29)	(33.50)	(32.76)	(31.58)
TREAT*POST Interaction	15.00	13.43	-6.816	12.03	-6.179	-12.04	-10.55
	(69.89)	(68.62)	(53.65)	(66.49)	(51.62)	(48.69)	(47.42)
Quarterly VC Inflow	0.00654		0.00757		0.00765		
	(0.0106)		(0.00988)		(0.00988)		
VC Firm Experience		2.455	-1.413			-3.575	
		(9.362)	(8.108)			(7.412)	
Constant	148.2***	153.5***	124.6**	161.2***	119.5***	147.4***	135.1***
	(39.05)	(35.36)	(38.76)	(35.47)	(35.36)	(30.36)	(27.63)
Observations	174	174	174	174	174	174	174
R-squared	0.095	0.089	0.067	0.089	0.067	0.059	0.059
Fund Stage Ctrl	YES	YES	NO	YES	NO	NO	NO
Quarterly Inflow Ctrl	YES	NO	YES	NO	YES	NO	NO
Experience Ctrl	NO	YES	YES	NO	NO	YES	NO
Year FE	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table provides the results of regressions for already-established firms for the dependent variable of fund size on middle size channel category VC funds. This table displays results of regressions in this size channel category that differ based on the combinations of controls (quarterly inflow/capital raised, VC firm experience, fund stage) included or left out to see if the inclusion or absence of certain controls affect analysis. Clustered robust standard errors by year.

Table E: DiD for Fund Size for Mega-Size Already-Established Firms (Taking out Controls)

VARIABLES	(1) FS & QInflow	(2) FS & EXP	(3) QInflow & EXP	(4) FS	(5) QInflow	(6) EXP	(7) No Control
TREAT	325.0	322.3	421.5	346.1	412.8	424.3	415.5
	(346.8)	(433.5)	(292.6)	(317.7)	(267.5)	(307.5)	(258.8)
TREAT*POST Interaction	430.8	381.3	355.4	369.5	360.7	341.8	346.8
	(550.6)	(291.0)	(484.5)	(280.1)	(527.5)	(300.3)	(306.4)
Quarterly VC Inflow	0.00938		0.00209		0.00217		
	(0.0539)		(0.0475)		(0.0479)		
VC Firm Experience		12.46	-5.790			-5.967	
		(110.5)	(89.03)			(91.30)	
Constant	592.0	612.2**	619.7**	632.9*	610.6*	626.9*	617.8**
	(492.0)	(253.9)	(264.4)	(336.1)	(303.4)	(284.2)	(258.8)
Observations	57	57	57	57	57	57	57
R-squared	0.142	0.141	0.134	0.141	0.134	0.134	0.134
Fund Stage Ctrl	YES	YES	NO	YES	NO	NO	NO
Quarterly Inflow Ctrl	YES	NO	YES	NO	YES	NO	NO
Experience Ctrl	NO	YES	YES	NO	NO	YES	NO
Year FE	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table provides the results of regressions for already-established firms for the dependent variable of fund size on mega size channel category VC funds. This table displays results of regressions in this size channel category that differ based on the combinations of controls (quarterly inflow/capital raised, VC firm experience, fund stage) included or left out to see if the inclusion or absence of certain controls affect analysis. Clustered robust standard errors by year.

Table F: DiD for Industry Shift for Low-Size Already-Established Firms (Taking out Controls)

VARIABLES	(1) FS & QInflow	(2) FS & EXP	(3) QInflow & EXP	(4) FS	(5) QInflow	(6) EXP	(7) No Control
TREATMENT	-0.0379	-0.0373	-0.0305	-0.0422	-0.0334	-0.0332	-0.0382
	(0.0976)	(0.0936)	(0.104)	(0.0949)	(0.104)	(0.102)	(0.102)
Quarterly VC Inflow	4.01e-06		4.37e-06		4.68e-06		
	(6.33e-06)		(5.86e-06)		(5.98e-06)		
VC Firm Experience		-0.00732	-0.00483			-0.00746	
		(0.0106)	(0.00796)			(0.0102)	
Constant	-0.0152	0.0124	0.0142	0.00750	0.00941	0.0425	0.0382
	(0.111)	(0.101)	(0.112)	(0.0977)	(0.111)	(0.103)	(0.102)
Observations	123	123	123	123	123	123	123
R-squared	0.081	0.078	0.063	0.076	0.062	0.056	0.054
Fund Stage Ctrl	YES	YES	NO	YES	NO	NO	NO
Quarterly Inflow Ctrl	YES	NO	YES	NO	YES	NO	NO
Experience Ctrl	NO	YES	YES	NO	NO	YES	NO
Year FE	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

This table provides the results of regressions for already-established firms for the dependent variable of industry shift on low size channel category VC funds. This table displays results of regressions in this size channel category that differ based on the combinations of controls (quarterly inflow/capital raised, VC firm experience, fund stage) included or left out to see if the inclusion or absence of certain controls affect analysis. Clustered robust standard errors by year.

Table G: DiD for Industry Shift for Middle-Size Already-Established Firms (Taking out Controls)

VARIABLES	(1) FS & QInflow	(2) FS & EXP	(3) QInflow & EXP	(4) FS	(5) QInflow	(6) EXP	(7) No Control
TREATMENT	0.0665	0.0619	0.0585	0.0682	0.0649	0.0609	0.0663
	(0.0460)	(0.0421)	(0.0380)	(0.0468)	(0.0414)	(0.0394)	(0.0422)
Quarterly VC Inflow	3.15e-06		5.33e-06		3.40e-06		
	(3.28e-06)		(3.99e-06)		(3.13e-06)		
VC Firm Experience		0.0344*	0.0325			0.0311	
		(0.0165)	(0.0179)			(0.0174)	
Constant	-0.00326	-0.111	-0.128	0.00352	-0.00627	-0.110	0.00129
	(0.0387)	(0.0688)	(0.0796)	(0.0340)	(0.0410)	(0.0700)	(0.0369)
Observations	174	174	174	174	174	174	174
R-squared	0.023	0.052	0.051	0.022	0.022	0.047	0.021
Fund Stage Ctrl	YES	YES	NO	YES	NO	NO	NO
Quarterly Inflow Ctrl	YES	NO	YES	NO	YES	NO	NO
Experience Ctrl	NO	YES	YES	NO	NO	YES	NO
Year FE	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table provides the results of regressions for already-established firms for the dependent variable of industry shift on middle size channel category VC funds. This table displays results of regressions in this size channel category that differ based on the combinations of controls (quarterly inflow/capital raised, VC firm experience, fund stage) included or left out to see if the inclusion or absence of certain controls affect analysis. Clustered robust standard errors by year.

Table H: DiD for Industry Shift for Mega-Size Already-Established Firms (Taking out Controls)

VARIABLES	(1) FS & QInflow	(2) FS & EXP	(3) QInflow & EXP	(4) FS	(5) QInflow	(6) EXP	(7) No Control
TREATMENT	-0.0920*	-0.159***	-0.126**	-0.0928*	-0.0852*	-0.121***	-0.0796*
	(0.0476)	(0.0449)	(0.0391)	(0.0410)	(0.0439)	(0.0325)	(0.0374)
Quarterly VC Inflow	-7.29e-06		-6.78e-06**		-6.85e-06**		
	(4.11e-06)		(2.22e-06)		(2.31e-06)		
VC Firm Experience		0.0414***	0.0338*			0.0339**	
		(0.00982)	(0.0148)			(0.0145)	
Constant	0.113	-0.0170	-6.94e-05	0.0650	0.0609	-0.0367	0.0240
	(0.0945)	(0.0500)	(0.0477)	(0.0821)	(0.0452)	(0.0421)	(0.0374)
Observations	57	57	57	57	57	57	57
R-squared	0.291	0.390	0.349	0.264	0.255	0.323	0.228
Fund Stage Ctrl	YES	YES	NO	YES	NO	NO	NO
Quarterly Inflow Ctrl	YES	NO	YES	NO	YES	NO	NO
Experience Ctrl	NO	YES	YES	NO	NO	YES	NO
Year FE	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table provides the results of regressions for already-established firms for the dependent variable of industry shift on mega size channel category VC funds. This table displays results of regressions in this size channel category that differ based on the combinations of controls (quarterly inflow/capital raised, VC firm experience, fund stage) included or left out to see if the inclusion or absence of certain controls affect analysis. Clustered robust standard errors by year.

Table I: Robustness Check for DiD for Fund Size for Already-Established Firms with Cutoff One Year Prior in 2015

VARIABLES	(1) Low Size Channel All Controls	(2) Low Size Channel 2016 All Controls	(3) Low Size Channel 2017 All Controls	(4) Middle Size Channel All Controls	(5) Middle Size Channel 2016 All Controls	(6) Middle Size Channel 2017 All Controls	(7) Mega Size Channel All Controls	(8) Mega Size Channel 2016 All Controls	(9) Mega Size Channel 2017 All Controls
TREAT*POST Interaction	9.451	-1.838	1.099	6.912	16.70	-33.53	459.0	154.4	-1,752
	(8.131)	(16.01)	(6.493)	(50.18)	(43.70)	(111.9)	(379.0)	(109.2)	(5,791)
Observations	141	42	47	172	81	68	64	39	17
R-squared	0.185	0.303	0.557	0.137	0.422	0.195	0.200	0.426	0.393

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table provides the robustness check results of regressions for already-established firms for the dependent variable of fund size on each size channel category (low, middle, mega) of VC funds, with cutoff moved one year earlier to 2015. For each size channel category, two more regressions are run on only the funds with initial closing in 2016 and then only the funds with initial closing in 2017. All controls (quarterly inflow/capital raised, VC firm experience, fund stage) and year fixed effects are used in these regression results. Clustered robust standard errors by year.

Table J: Robustness Check Analysis for Fund Size for Newly-Established Firms with Cutoff One Year Prior in 2015

VARIABLES	(1) Overall Yearly All Control	(2) Overall Yearly No Control	(3) Lower Yearly All Control	(4) Lower Yearly No Control	(5) Middle Yearly All Control	(6) Middle Yearly No Control	(7) Mega Yearly All Control	(8) Mega Yearly No Control
TREAT*POST Interaction	34.11	34.11	5.179	5.179	31.04	31.04	-458.6*	-355.9
	(38.33)	(37.17)	(3.450)	(3.515)	(20.62)	(24.72)	(226.3)	(332.8)
Observations	18	18	18	18	18	18	12	14
R-squared	0.442	0.439	0.288	0.225	0.786	0.679	0.703	0.406

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table provides the robustness check results of regressions for newly-established firms for the dependent variable of fund size on each size channel category (low, middle, mega) of VC funds as well as on the overall full sample, with cutoff moved one year earlier to 2015. This table displays results of regressions both with the control of yearly inflows into VC as well as without.

Table K: Robustness Check for DiD for Industry Shift for Already-Established Firms with Cutoff One Year Prior in 2015

VARIABLES	(1) Low Size Channel All Controls	(2) Low Size Channel 2016 All Controls	(3) Low Size Channel 2017 All Controls	(4) Middle Size Channel All Controls	(5) Middle Size Channel 2016 All Controls	(6) Middle Size Channel 2017 All Controls	(7) Mega Size Channel All Controls	(8) Mega Size Channel 2016 All Controls	(9) Mega Size Channel 2017 All Controls
TREATMENT	-0.200	-	-0.435***	0.0722**	0.0399	0.185***	-0.157***	-0.116**	0.0953
	(0.109)		(0.0186)	(0.0245)	(0.0258)	(0.0359)	(0.0291)	(0.0444)	(0.389)
Observations	141	42	47	172	81	68	64	39	17
R-squared	0.112	0.118	0.312	0.140	0.493	0.411	0.403	0.412	0.798

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table provides the robustness check results of regressions for already-established firms for the dependent variable of industry shift on each size channel category (low, middle, mega) of VC funds, with cutoff moved one year earlier to 2015. For each size channel category, two more regressions are run on only the funds with initial closing in 2016 and then only the funds with initial closing in 2017. All controls (quarterly inflow/capital raised, VC firm experience, fund stage) and year fixed effects are used in these regression results. Clustered robust standard errors by year.

Table L: Robustness Check Analysis for Industry Shift for Newly-Established Firms with Cutoff One Year Prior in 2015

VARIABLES	(1) Overall Yearly All Control	(2) Overall Yearly No Control	(3) Lower All Control	(4) Lower No Control	(5) Middle All Control	(6) Middle No Control	(7) Mega All Control	(8) Mega No Control
TREAT*POST Interaction	1.200	1.200	0.550	0.550	1.400	1.400	-1.469	-1.500
	(13.33)	(15.40)	(8.266)	(8.874)	(6.241)	(7.735)	(1.709)	(1.611)
Observations	18	18	18	18	18	18	12	12
R-squared	0.879	0.822	0.871	0.835	0.818	0.701	0.423	0.409

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table provides the robustness check results of regressions for newly-established firms for the dependent variable of industry shift on each size channel category (low, middle, mega) of VC funds as well as on the overall full sample, with cutoff moved one year earlier to 2015. This table displays results of regressions both with the control of yearly inflows into VC as well as without.

Table M: Robustness Check for DiD for Fund Size for Already-Established Firms with Cutoff One Year Later in 2017

VARIABLES	(1) Low Size Channel All Controls	(2) Low Size Channel 2018 All Controls	(3) Low Size Channel 2019 All Controls	(4) Middle Size Channel All Controls	(5) Middle Size Channel 2018 All Controls	(6) Middle Size Channel 2019 All Controls	(7) Mega Size Channel All Controls	(8) Mega Size Channel 2018 All Controls	(9) Mega Size Channel 2019 All Controls
TREAT*POST Interaction	25.04	5.277	-31.44	-46.56	-95.61	-50.16	-1,283**	-1,152*	3,370***
	(27.20)	(7.240)	(31.61)	(26.22)	(75.66)	(98.18)	(494.5)	(560.6)	(460.3)
Observations	95	47	30	130	72	55	54	38	22
R-squared	0.199	0.271	0.620	0.211	0.278	0.095	0.193	0.282	0.690

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table provides the robustness check results of regressions for already-established firms for the dependent variable of fund size on each size channel category (low, middle, mega) of VC funds, with cutoff moved one year later to 2017. For each size channel category, two more regressions are run on only the funds with initial closing in 2018 and then only the funds with initial closing in 2019. All controls (quarterly inflow/capital raised, VC firm experience, fund stage) and year fixed effects are used in these regression results. Clustered robust standard errors by year.

Table N: Robustness Check Analysis for Fund Size for Newly-Established Firms with Cutoff One Year Later in 2017

VARIABLES	(1) Overall Yearly All Control	(2) Overall Yearly No Control	(3) Lower Yearly All Control	(4) Lower Yearly No Control	(5) Middle Yearly All Control	(6) Middle Yearly No Control	(7) Mega Yearly All Control	(8) Mega Yearly No Control
TREAT*POST Interaction	37.62	37.62	8.718***	8.718***	26.51	26.51		
	(29.74)	(28.15)	(2.258)	(2.438)	(25.01)	(23.86)		
Observations	18	18	18	18	18	18	12	14
R-squared	0.339	0.297	0.390	0.348	0.492	0.489	0.680	0.350

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table provides the robustness check results of regressions for newly-established firms for the dependent variable of fund size on each size channel category (low, middle, mega) of VC funds as well as on the overall full sample, with cutoff moved one year later to 2017. This table displays results of regressions both with the control of yearly inflows into VC as well as without.

Table O: Robustness Check for DiD for Industry Shift for Already-Established Firms with Cutoff One Year Later in 2017

VARIABLES	(1) Low Size Channel All Controls	(2) Low Size Channel 2018 All Controls	(3) Low Size Channel 2019 All Controls	(4) Middle Size Channel All Controls	(5) Middle Size Channel 2018 All Controls	(6) Middle Size Channel 2019 All Controls	(7) Mega Size Channel All Controls	(8) Mega Size Channel 2018 All Controls	(9) Mega Size Channel 2019 All Controls
TREATMENT	-0.0306	-0.0355*	0.103	0.0204	0.0894	0.0195	-0.116***	-0.0543**	-
	(0.0922)	(0.0160)	(0.0693)	(0.0344)	(0.0900)	(0.0427)	(0.0339)	(0.0175)	
Observations	95	47	30	130	72	55	54	38	22
R-squared	0.132	0.270	0.423	0.114	0.204	0.419	0.319	0.648	0.479

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table provides the robustness check results of regressions for already-established firms for the dependent variable of industry shift on each size channel category (low, middle, mega) of VC funds, with cutoff moved one year later to 2017. For each size channel category, two more regressions are run on only the funds with initial closing in 2018 and then only the funds with initial closing in 2019. All controls (quarterly inflow/capital raised, VC firm experience, fund stage) and year fixed effects are used in these regression results. Clustered robust standard errors by year.

Table P: Robustness Check Analysis for Industry Shift for Newly-Established Firms with Cutoff One Year Later in 2017

VARIABLES	(1) Overall Yearly All Control	(2) Overall Yearly No Control	(3) Lower All Control	(4) Lower No Control	(5) Middle All Control	(6) Middle No Control	(7) Mega All Control	(8) Mega No Control
TREAT*POST Interaction	2.143	2.143	-2.500	-2.500	6.143	6.143		
	(22.10)	(24.92)	(11.79)	(13.78)	(10.12)	(11.14)		
Observations	18	18	18	18	18	18	12	12
R-squared	0.873	0.823	0.889	0.833	0.765	0.711	0.417	0.365

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table provides the robustness check results of regressions for newly-established firms for the dependent variable of industry shift on each size channel category (low, middle, mega) of VC funds as well as on the overall full sample, with cutoff moved one year later to 2017. This table displays results of regressions both with the control of yearly inflows into VC as well as without.

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