How does Venture Capital Financing Improve Efficiency in Private Firms? A Look Beneath the Surface

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Abstract

We use the Longitudinal Research Database (LRD) of the U.S. Census Bureau, which covers the universe of private and public U.S. manufacturing firms, to study several related questions regarding the efficiency gains generated by venture capital (VC) investment in private firms. First, do VCs indeed improve the efficiency (total factor productivity, TFP) of private firms, and if so, are certain kinds of VCs (high reputation vs. low reputation) better at generating such efficiency gains than others? Second, do VCs invest in more efficient firms to begin with (screening) or do they improve efficiency after investment (monitoring)? Third, do efficiency improvements due to VC backing arise from increases in sales or reductions in costs? Fourth, do such efficiency gains affect the probability of a successful exit (IPO or acquisition) for VC-backed firms? Our analysis shows that the overall efficiency of VC-backed firms is higher than that of non-VC-backed firms at every point in time. This efficiency advantage of VC-backed firms arises from both screening and monitoring: the efficiency of VC-backed firms prior to receiving financing is higher than that of non-VC-backed firms and further, the growth in efficiency subsequent to receiving VC financing is greater for such firms relative to non-VC-backed firms. The above increases in efficiency of VC-backed firms are spread over the first two rounds of VC financing after which the TFP of such firms remains constant till exit. Further, we show that while the TFP of firms prior to receiving financing is lower for high-reputation VC-backed firms, the increase in TFP subsequent to financing is significantly greater for these firms, consistent with high-reputation VCs having greater monitoring ability. We disentangle the screening and monitoring effects of VC backing using three different methodologies: switching regression with endogenous switching; regression discontinuity analysis; and propensity score matching. We show that while overall efficiency gains generated by VC backing arise primarily from improvements in sales, the efficiency gains of high-reputation VC-backed firms arise also from lower increases in production costs. Finally, we show that both screening and monitoring activities of VCs positively affect the probability of a successful exit (IPO or acquisition).

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1 Introduction

The role of venture capital (VC) financing in creating value for entrepreneurial firms has been widely debated in both the academic and practitioner literature. In particular, several authors in the theoretical VC literature have argued that, in addition to providing financing, VCs provide other services to private firms which can considerably enhance the probability of success of these firms (see, e.g., Chemmanur and Chen (2003)). There is also a theoretical literature which analyzes how such value creation differs across different types of VCs (e.g., Fulghieri and Sevilir (2008)), and the relationship between the optimal size of a VC's portfolio and the VC's ability to add value to its portfolio firms (Fulghieri and Sevilir (2009)). Another theoretical literature argues that access to private financing (such as venture capital) can significantly affect the extent of innovation and therefore the productivity of a private firm when it faces competition from other firms in the product market. A prominent example of this literature is Spiegel and Tookes (2008). Their model predicts that firms will finance projects with the greatest revenue-generating ability privately (e.g., under venture financing), and will then go to the public markets only when more modest innovations remain. Practitioners also argue that in addition to providing funding for private firms, VCs contribute greatly to their success in many other ways, for example, by helping them in hiring competent management, providing better incentives to firm management and employees, as well as by allowing them access to their network of contacts among suppliers and potential customers in the product market. Further, both academics and practitioners have argued that high-reputation VCs are better at providing the above services than low-reputation VCs.[1] Despite the above large theoretical and practitioner literature which argues that VCs may create significant value in the product market, empirical evidence on whether VCs indeed create such value has been scarce, perhaps due to limitations on the availability of data on private firms.

This paper addresses the above gap in the empirical literature by conducting the first large sample study and analyzing the role of venture capitalists in creating productivity improvements for entrepreneurial firms using a unique database covering the universe of private firms in the U.S. manufacturing

[1] See, e.g., Bygrave and Timmons (1992), who states, "It is far more important whose money you get than how much you get or how much you pay for it."

sector obtained from the Longitudinal Research Database (LRD) of the U.S. Bureau of Census. Manufacturing firms account for approximately 41% of the total number of VC-backed firms on *VentureXpert* and approximately 31% of all VC financing rounds with total VC investment in these firms being above $150 billion: some prominent examples of manufacturing firms that have received VC financing in the past are Advanced Micro Devices (AMD), Cisco Systems, Genentech, Genzyme, Texas Instruments, Imclone, Mattel, Dell, and Sun Microsystems. We answer several interesting questions regarding the role played by VCs in creating "extra-financial" value for private firms that they invest in. First, we study whether VCs indeed create such value for entrepreneurial firms, and if so, how and when this value is created. We answer the following questions in this part of the paper: First, do VC-backed firms have better performance and higher operating efficiency (as measured by Total Factor Productivity) than non-VC-backed firms? Second, if indeed this is the case, precisely how do VCs create value for private firms: are they able to identify and invest in higher quality entrepreneurial firms, i.e., "screening", or does the value creation arise primarily from the various extra-financial value-added services they provide to the firm (discussed earlier) subsequent to their investing in the firm, i.e., "monitoring"?[2] Third, are more reputable VCs capable of creating greater value by improving the efficiency of firms they invest in? In particular, are high-reputation VCs better at screening or monitoring (or both) than low-reputation VCs? Finally, if the value-addition due to VC backing is at least partly due to monitoring, how are these value improvements spread over time: do they occur in the early stages immediately after the VCs invest in the firm, or do they occur in later stages?

Further, we identify the precise channels through which VCs improve the productivity of private firms. In particular, we answer the following questions: Do these efficiency improvements arise from better aggregate product market performance (sales) of VC-backed firms relative to non-VC-backed firms? Or, do they arise from lower production costs of VC-backed firms relative to non-VC-backed firms?[3] In answering the above questions, we disentangle value creation by VCs through screening from value creation through monitoring in each of the above channels and benchmark against non-VC-backed firms. We also study whether efficiency improvements arising through the above channels are greater for firms backed by high-reputation VCs compared to those backed by low-reputation VCs. We also study how VC-backing and

[2] Note that by monitoring we generally refer to a variety of value-adding services provided by the VC and not explicitly to monitoring an investment in the strictest sense.

[3] For example, such efficiency improvements could arise from a lower aggregate level of employment in venture backed firms relative to non-venture backed firms, or through lower salaries and wages (or both), thus leading to lower total labor costs. Alternately, such improvements could also arise from more efficient usage of materials in the production process.

productivity improvements affect the probability of a successful exit (IPO or acquisition) rather than a write-off. In answering the above question, we distinguish between the probability of exit through an IPO versus that through an acquisition. In addition, we also disentangle the effect of higher productivity of VC-backed firms due to screening and efficiency gains generated by VCs due to monitoring, on the probability of a successful exit.

The results of our empirical analysis can be summarized as follows. We start by investigating whether VC-backed firms are characterized by greater overall efficiency compared to non-VC-backed firms. Similar to several other papers that have used the LRD database to study various corporate events (see, e.g., Schoar (2002), Maksimovich and Philips (2008), and Chemmanur, He, and Nandy (2010)), we use Total Factor Productivity (TFP) as our measure of firm efficiency. TFP measures the residual growth in a firm's output after accounting for the growth in output directly attributable to growth in the various factors of production and the production technology in place. In other words, an increase in TFP is an increase in the overall productivity (efficiency) of the firm, since more output can be produced now than earlier, even if the amounts of each of the factors of production remained the same. Venture capital financing involves the injection of additional capital into the firm which may increase the scale of the firm and thus a mechanical increase in output and revenue. Therefore, TFP is a particularly appropriate measure to analyze the increase in firm performance due to VC backing, since it captures productivity changes after accounting for increases in the scale of production, which will not be captured by more traditional measures such as revenue or sales growth. We find that the efficiency of VC-backed firms (as measured by TFP) prior to receiving venture financing is higher than that of non-VC-backed firms, and further, the growth in TFP subsequent to receiving venture financing is greater for VC-backed firms relative to non-VC-backed firms. We thus find evidence of both a screening and a monitoring role for VCs in improving firm efficiency.

In our analysis of the dynamics of productivity growth, we first show that the above improvement in TFP of VC-backed firms relative to non-VC-backed firms increases over the four years subsequent to the year of the first round of venture financing, and remains at this higher level till exit. We are the first paper to document the above finding in the literature. We also analyze the above dynamics in TFP changes round-by-round for VC-backed firms. The results of our round-by-round analysis are consistent with those discussed above and show that most of the efficiency gains for VC-backed firms are concentrated around the first couple of rounds of VC investment in the firm.

In order to clearly distinguish between the screening and monitoring effects of VC backing on

firm efficiency (and in the process address any potential endogeneity concerns related to VC backing), we employ three alternative methodologies. The first methodology we employ is "switching regressions with endogenous switching," which answers the following question: What would the TFP growth of VC-backed firms have been, had they not received such financing (and vice versa)? Clearly, the difference between the actual TFP growth of VC-backed firms and the hypothetical level estimated from the above "what if" analysis yields the TFP growth attributable to the monitoring effect of VC backing. Consistent with our earlier results, our switching regression results indicate a significantly positive effect of VC monitoring on TFP growth. Specifically, we find that TFP growth is smaller for VC-backed firms had they not received VC financing and TFP growth is greater for non-VC-backed firms had they received VC financing.

The second methodology we use to distinguish between screening and monitoring is a regression discontinuity analysis. This approach uses a discontinuous jump in the probability of obtaining VC financing to identify the causal effect of VC involvement on TFP growth. We exploit the eligibility requirements for firms to obtain financial support from the U.S. Small Business Administration (SBA) to identify a jump in the probability of VC financing, since firms that are not eligible for SBA support are more likely to seek external financing sources such as venture capital. Consistent with our previous results documenting the monitoring ability of VCs, we find a positive causal effect of VC financing on the TFP growth of private firms receiving such financing.

The third methodology we employ is a matched sample analysis using a propensity score matching algorithm. Using this methodology, we match our sample of VC-backed firms to non-VC-backed private firms along the following dimensions: firm size, industry, and average TFP growth over the five years prior to receiving venture financing. Consistent with our earlier results, we find that the TFP growth of VC-backed firms subsequent to receiving financing is significantly greater than that of matching firms, thus confirming the monitoring effect of VC backing on TFP growth.

Our results on the channels through which VC backing improves efficiency can be summarized as follows. First, VC-backed firms are characterized by higher sales than non-VC-backed firms prior to receiving venture financing. Further, these firms are characterized by a greater increase in sales in the years subsequent to receiving venture financing compared to non-VC-backed firms. Second, total production costs are greater for VC-backed firms compared to non-VC-backed firms prior to receiving venture financing; the growth in these costs subsequent to receiving financing is also greater for VC-backed firms relative to non-VC-backed firms. Third, while total employment is similar for VC-backed and non-VC-backed firms prior

to receiving venture financing, total salaries and wages are greater for VC-backed firms prior to receiving financing. Additionally, the growth in total salaries and wages subsequent to receiving financing is greater for VC-backed firms relative to non-VC-backed firms, though the growth in the level of employment remains comparable across the two kinds of firms. Overall, the above results indicate that on average, the primary channel through which VC backing improves efficiency is by improving product market performances (sales) and this increase in sales could partly be attributed to a better quality workforce employed by VC-backed firms.

We also find that, while the TFP of firms prior to VC financing is higher for low-reputation VC-backed firms, the growth in TFP subsequent to financing is higher for firms backed by high-reputation VCs relative to those backed by low-reputation VCs. This finding suggests that while low-reputation VCs rely on selecting more efficient firms to begin with (screening), it is the high-reputation VCs who have greater monitoring ability and are thus able to improve the efficiency of the firms they invest in. Consistent with these results, we find significantly higher TFP at every round subsequent to receiving financing for high-reputation VC-backed firms compared to low-reputation VC-backed firms. Further, the increase in TFP after receiving financing is significantly greater for firms backed by high-reputation VCs, again suggesting greater monitoring ability for such VCs.

Our findings regarding the differences between high-reputation and low-reputation VCs in terms of the channels through which they improve the efficiency of their portfolio firms can be summarized as follows. First, the level of sales prior to receiving financing is greater for high-reputation VC-backed firms compared to low-reputation VC-backed firms and the growth in sales subsequent to financing (in the first four years) is also greater for high-reputation VC-backed firms. Second, total production costs prior to venture financing is lower for high-reputation VC-backed firms compared to low-reputation VC-backed firms and the growth in total production costs subsequent to financing is also lower for high-reputation VC-backed firms compared to low-reputation VC-backed firms. The above two results indicate that high-reputation VCs are able to generate greater increases in sales (output) with lower increases in production costs, thus leading to greater improvements in the TFP of firms backed by them, compared to low-reputation VCs. Overall, these results are consistent with the notion that the primary channel through which both high and low-reputation VCs improve efficiency is through improvements in product market performance (sales); for high-reputation VCs, additional improvements in efficiency arise through reductions in input costs as well.

Finally, the results of our analysis on the impact of efficiency improvements of VC-backed firms

on the probability of a successful exit can be summarized as follows. First, VC financing has a positive association with the probability of a successful exit (either through an IPO or an acquisition). Second, the probability of an exit through an IPO is increasing in both the level of TFP prior to each year and the TFP growth; The above results are consistent with the notion that VC backing abd efficiency improvments have a long lived impact indeed result in higher likelihood of exit. They also suggest that firms with higher levels of efficiency improvements are more likely to exit through an IPO rather than an acquisition.[4]

The rest of this paper is organized as follows. Section 2 reviews the related literature and relates our paper to it. Section 3 describes the data, sample selection, and explains the construction of the different variables used in this study. Section 4 describes our empirical methodology and presents the results of our multivariate analysis relating VC involvement to increases in firm efficiency. Section 5 analyzes the channels through with TFP and efficiency improvements are generated for VC-backed firms. Section 6 analyzes how VC backing and improvement in efficiency impact the exit decision of the firm. Section 7 concludes.

2 Literature Review

With the exception of a few papers there is a complete lack of studies in the prior literature comparing VC-backed firms with non-VC-backed firms. These studies are Hellmann and Puri (2000, 2002) and Hsu (2006). Hellmann and Puri (2000) provide evidence that VC financing is related to the product market strategies and outcomes of start-ups, while Hellmann and Puri (2002) provide evidence regarding the profesionalization of start-up firms. Hsu (2006), analyzes the impact of VC backing on the commercialization strategies of technology based start-ups. However, to the best of our knowledge, this is the first paper in the literature that compares the efficiency of VC-backed and non-VC-backed private firms, and analyzes *how* and *when* efficiency improvements arise due to VC backing.

While prior studies in the literature have focused on the monitoring role of VCs based on samples of VC-backed firms, see, e.g., Lerner (1995), who examines VCs' representation on the boards of private firms and analyzes whether this representation is greater when the need for oversight is greater, we extend this literature by distinguishing between the screening and monitoring roles of venture capitalists; and directly comparing samples of VC-backed and non-VC-backed firms, as well as high-reputation VC-backed and low-

[4] See Bayar and Chemmanur (2006) for a theoretical model which makes the above prediction.

reputation VC-backed firms. Bengtsson and Ravid (2010) document how VC contracts vary geographically with California contracts having fewer investor-friendly contingencies. To the extent that value created by venture capitalists is manifested as abnormal returns to limited partners who invest in venture capital funds, our paper is also related to Lerner, Schoar, and Wongsunwai (2007) who analyze the differences in the returns accruing to various limited partners investing in VC funds.[5] In addition, activism at the VC partner level is also positively related to the success of VC portfolio companies (Bottazzi et al., 2008). Finally, the effect of VC backing on IPOs has been documented by several papers. Megginson and Weiss (1991) study the certification role of venture backing in the financing of IPOs. More recently, using a sample of venture backed firms, Sorensen (2007) shows that companies funded by more experienced VCs are more likely to go public. He documents that this follows both from the direct influence of more experienced VCs and also from sorting in the market. Our paper also contributes to the emerging literature on the role of financial intermediaries in the birth, growth, and death of entrepreneurial firms: see, e.g., Kerr and Nanda (2009).[6]

In a contemporaneous related paper, Puri and Zarutskie (2009) study the life cycle dynamics of VC-backed and non-VC-backed firms and examine the importance of VC in new firm creation. Their results show that VCs typically invest in firms that exhibit potential for large scale prior to exit and that VC-financed firms grow more rapidly than non-VC financed firms. They also analyze survival of VC financed firms and show that VC-financed firms are less likely to fail in the first four years after first receiving funding, but conditional on surviving past this point become more likely to fail relative to non-VC-financed firms. Our study differs from theirs along several dimensions as unlike their study, we focus on distinguishing between the screening and monitoring effects of VC backing and how such activities affect firm productivity.

[5] Our paper is also related to Gompers and Lerner (1999) who find that profit shares are higher for older and larger VCs, and Kaplan and Schoar (2005), who analyze both VC and buyout fund returns and show that there is a large degree of heterogeneity among fund returns and returns tend to improve with the experience of the general partner.

[6] Our paper is also related to the literature on firm's choice between private and public sources of financing: see, e.g., Spiegel and Tookes (2008) and Chemmanur and Fulghieri (1999). To the extent that we also study the propensity of venture backed firms to exit through IPOs, our paper is also related to the broader literature on IPOs: see Ritter and Welch (2002) for a review of this literature.

3 Data, Sample Selection, and Construction of Variables

The primary data used in this study is obtained from the Longitudinal Research Database (LRD), maintained by the Center of Economic Studies at the U.S. Bureau of Census.[7] The LRD is a large micro database which provides plant level information for firms in the manufacturing sector (SIC codes 2,000 to 3,999).[8] In the census years (1972, 1977, 1982, 1987, 1992, 1997), the LRD covers the entire universe of manufacturing plants in the Census of Manufacturers (CM). In non-census years, the LRD tracks approximately 50,000 manufacturing plants every year in the Annual Survey of Manufacturers (ASM), which covers all plants with more than 250 employees with probability one. In addition, it also includes smaller plants that are randomly selected every fifth year to complete a rotating five year panel. Therefore, all U.S. manufacturing plants with more than 250 employees are included in the LRD database on a yearly basis from 1972 to 2000, and smaller plants with fewer than 250 employees are included in the LRD database every census year and are also randomly included in the non-census years, continuously for five years, as a rotating five year panel.[9] Most of the data items reported in the LRD (e.g., the number of employees, employee compensation, and total value of shipments) represent items that are also reported to the IRS, increasing the accuracy of the data.

The two major difficulties in conducting research on VC financing and its effects on firms' performance are first, obtaining firm specific data on private firms that do receive VC financing, and second, obtaining data on private firms that could potentially use VC but do not. Clearly, publicly available firm level data, such as COMPUSTAT does not meet this criteria since it only has data on public firms. An alternate data source is another panel data set collected by the U.S. Census Bureau, namely the Longitudinal Business Database (LBD).[10] The major advantages of using the LRD relative to the LBD for this study are the following: First, assets, sales, operating costs, and other such firm level financial information are either not covered or mostly missing in the LBD compared to the LRD. Thus, our overall metric of

[7] See McGuckin and Pascoe (1988) who provide a detailed description of the Longitudinal Research Database (LRD) and the method of data collection.

[8] It should be noted that approximately 62% of the hi-tech industries, comprising of Computers, Telecom, Biotech, and others, in which VC's are more inclined to invest - as anecdotal evidence suggests, fall within the scope of the LRD, as these industries are part of the manufacturing sector, having 4-digit SIC codes between 2000 and 3999.

[9] Given that a random sample of smaller plants is continuously present in our sample; our data is not substantially skewed towards larger firms, smaller firms are well represented in the data. The rotating sample of smaller plants is sampled by the Census Bureau each year in the non-census years in order to minimize such a bias in the data. We address this issue further in Panel B of Table 2 which is discussed in the next section.

[10] Similar to the LRD, the LBD is also a panel data set that tracks the set of U.S. business establishments from 1975 to the present. While the LRD is limited to the manufacturing sector, the LBD encompasses all industry sectors. However, the LBD is not well suited for the aim of our study. We elaborate on this issue further below.

firm efficiency, i.e., total factor productivity (TFP) can only be constructed for the LRD panel. Second, the nature of the LRD allows us to identify the precise channels of value improvements in firms resulting from VC investments, which would not have been possible had we used the LBD. Due to these reasons we focus on the LRD for the purposes of this study.

Our sample of VC investments is drawn from *VentureXpert*, a database maintained by Thomson Financial which contains round by round information for both the firms in which VCs invest as well as the VC firms themselves. It provides information on the names and locations of VCs who invest in each round of the firm, the number of such VCs, the total amount invested per round, and also the date of each round of investment. Our initial extract from *VentureXpert* gives us a sample of 12,481 U.S. based firms whose first round of VC financing lies between 1972 and 2000. We first remove from our sample any investment made by VC funds for buyout or acquisition purposes or where the purpose of the first round of investment was unknown or missing. We then merge this sample of firms to the Standard Statistical Establishment List (SSEL), which is a list of business establishments in the U.S. maintained by the U.S. Census Bureau and updated on an annual basis.[11] We employ standard matching procedures using the names and addresses of firms that is commonly used by U.S. Census Bureau researchers and those working with these databases, which yields a positive match for 10,355 firms, giving us a match rate of about 83%.[12] We then restrict the sample to the manufacturing sector (SIC codes 2,000 to 3,999), and merge to the LRD. We keep only those firms for which we have detailed information to calculate TFP at the 4-digit SIC and annual level, which leaves us with a final sample of 1,881 VC-backed firms representing 16,824 firm-years of data. This sample represents approximately 36% of the VC-backed manufacturing firms from *VentureXpert*.[13] Panel A of Table 1 presents the industry distribution at the 2 digit SIC level of the firms

[11] The SSEL is the Business Register or the "master" data set of the U.S. Census Bureau from which both the LRD and the LBD are constructed. The SSEL contains data from the U.S. government administrative records, such as tax returns, and is augmented with data from various Census surveys. The SSEL data is at the establishment level - an establishment is a single physical location where business is conducted. The SSEL provides names and addresses of establishments and also numerical identifiers at both the establishment level as well as the firm level, through which one can link the SSEL to the LRD. Both the SSEL and the LRD provides a permanent plant number (PPN) and a firm identifier (FID) both of which remain invariant through time. We use these identifiers to track the plants and the firms forwards and backwards in time. A good description of the SSEL can be found in Jarmin and Miranda (2002).

[12] This match rate is comparable to that acheived by earlier studies, such as Chemmanur, He, and Nandy (2010) and Puri and Zarutskie (2009) who provide a detailed description of the matching procedures employing name and address matching.

[13] In unreported tests, we compare our LRD matched sample to the rest of the VC-backed manufacturing sample, based on information available from *VentureXpert*. We find that on average our sample is representative of manufacturing firms in *VentureXpert*. In particular, our sample of LRD matched firms receive similar amounts of VC funding (first round as well as total funding) over a similar number of rounds compared to non-LRD matched firms. One difference is with respect to the proportion of early stage investments, while it is 42% in our LRD matched sample, the non-LRD matched sample has about 60% of firms receiving early stage investments. We therefore provide a robustness check of our results by separately conducting our analysis for early and late stage firms.

that received VC financing in our sample while panel B presents the number of firms that received their first round of VC financing in any given year over our sample period. As can be seen from this table, our matched sample of VC-backed firms is representative of what anecdotal evidence suggests, with high levels of concentration in computers, biotech, electronics, and other high-tech industries such as precision instruments. However, non-packaged software, e-commerce, non-manufacturing high-tech firms, and other service oriented firms, such as financial firms, are not included in our sample. In addition, consistent with anecdotal evidence, one can also observe that VC investment in new firms increased during the internet bubble period of the late 90's. Thus, in this respect, our matched sample of VC-backed manufacturing firms in the LRD is generally representative of the overall population of VC-backed firms in the U.S.

Furthermore, since the objective of our paper is to analyze the impact of VC investments to private entrepreneurial firms, we also identified all public firms (as defined by CRSP), for every year in our sample and removed them from the LRD by using a similar matching approach. Thus, at any given year within our sample, we are left with only private firms all of whom could potentially receive VC funding; giving us a sample of 185,882 non-VC-backed firms, representing 771,830 firm-years of data.[14,15]

3.1 Measurement of Total Factor Productivity (TFP)

The primary measure of firm efficiency used in our analysis is Total Factor Productivity (TFP) which is calculated from the LRD for each individual plant at the annual four-digit (SIC) industry level as in Chemmanur, He, and Nandy (2010). The total factor productivity of the firm for each year is then calculated as a weighted sum of plant Total Factor Productivity (TFP). Increasingly, several recent papers in the corporate finance literature have used this approach to measure TFP, see, e.g., Schoar (2002), Maksimovic and Philips (2008) among others. We obtain measures of TFP at the plant level, by estimating a log-linear Cobb-Douglas production function for each industry and year. Industry is defined at the level of four-digit SIC codes.[16] Individual plants are indexed i; industries j; for each year t, in the sample:

[14] Note that some public firms may re-enter our sample if they went through an LBO/MBO or otherwise became private again. As mentioned above, we remove any firms that received VC funding where the primary reason is for acquisition or buyout. Thus, if any of these firms received VC funding during the process of becoming private, then they are eliminated from our data; if on the other hand they were not involved in a buyout with funding from VC's, we retain them in the data.

[15] It should be noted that both the SSEL and the LRD provide establishment-level, i.e., plant-level data. For the purpose of our analysis we aggregate this data to the firm level using standard techiniques used in the literature previously (for example, see Chemmanur, He, and Nandy (2009)) and numerical identifiers for plants and firms provided in the LRD, which we discuss further below.

[16] As a robustness check, we re-estimate the production function in several different ways. First, we use two and three-digit SIC industry classifications. Second, we estimate TFP with value added production function specifications and separate white and blue collar labor inputs. Third, we divide each annual four-digit SIC industry into two groups based on capital intensity,

$$\ln(Y_{ijt}) = \alpha_{jt} + \beta_{jt}\ln(K_{ijt}) + \gamma_{jt}\ln(L_{ijt}) + \delta_{jt}\ln(M_{ijt}) + \varepsilon_{ijt} \quad (1)$$

We use the LRD data to construct as closely as possible the variables in the production function. Output (Y) is constructed as plant sales (total value of shipments in the LRD) plus changes in the value of inventories for finished goods and work-in-progress. Since we appropriately deflate plant sales by the annual industry specific price deflator, our measure should be proportional to the actual quantity of output.[17]

Labor input (L) is defined as production worker equivalent man hours, that is, the product of production worker man-hours, and the ratio of total wages and salaries to production worker wages. We also re-estimate the TFP regression by specifying labor input to separately include non-production workers, which yields qualitatively similar results. Values for capital stock (K) are generated by the recursive perpetual inventory formula. We use the earliest available book value of capital as the initial value of net stock of plant capital (this is either the value in 1972, or the first year a plant appears in the LRD sample). These values are written forward annually with nominal capital expenditure (appropriately deflated at the industry level) and depreciated by the economic depreciation rate at the industry level obtained from the Bureau of Economic Analysis. Since values of all these variables are available separately for buildings and machinery, we perform this procedure separately for each category of assets. The resulting series are then added together to yield our capital stock measure.

Finally, material input (M) is defined as expenses for the cost of materials and parts purchased, resales, contract work, and fuel and energy purchased, adjusted for the change in the value of material inventories. All the variables are deflated using annual price deflators for output, materials, and investment at the four-digit SIC level from the Bartelsman and Gray NBER Productivity Database.[18] Deflators for capital stock are available from the Bureau of Economic Analysis.[19] We ensure that each of the inputs have a non-zero reported value. Plant level TFP is then computed as the residuals of regression (1), estimated

i.e., plants with capital intensity greater than the median capital intensity for that annual four-digit group are put in one group, while those with capital intensity less than the median are put in another group. We then estimate the production function for each group separately. In all cases we find qualitatively equivalent results.

[17] Thus, the dispersion of TFP for firms in our sample should almost entirely reflect dispersions in efficiency. For the purposes of this study however, it does not matter even if a portion of the change in TFP arises from changes in prices for VC backed firms. For example, VCs may be able to obtain higher prices for the products of the firms they invest in, compared to those of non-VC backed firms. However, even if an increase in price partially leads to an increase in TFP for VC backed firms, such an increase in TFP can still be considered an extra-financial value-added service (monitoring - as defined by us) that VC backed firms obtain due to their affiliation with the VC.

[18] See Bartelsman and Gray (1996) for details.

[19] For a detailed description of the construction of TFP measures from LRD variables see Lichtenberg (1992).

separately for each year and each four-digit SIC industry.

This measure of TFP is more flexible than the cash-flow measure of performance, as it does not impose the restriction of constant returns to scale and constant elasticity of scale. Also, since coefficients on capital, labor, and material inputs can vary by industry and year, this specification allows for different factor intensities in different industries. These production function estimates are pooled across the entire universe of manufacturing plants in the LRD, including plants belonging to both public and private firms and irrespective of whether they received VC financing or not, thus giving us an accurate measure of the relative performance of a plant within a particular 4-digit SIC industry in any given year. The TFP measure for each individual plant is the estimated residual of these regressions and therefore by construction the average TFP (i.e., the average of the residuals) in any 4-digit SIC industry-year is zero.

Intuitively, TFP can be understood as the difference between the actual output produced by the plant compared to its "predicted output". This "predicted output" is what the plant should have produced, given the amount of inputs it used and the industry production technology in place. Hence a plant that produces *more* than the predicted amount of output in any given year has a greater than average productivity for that year, whereas a plant that produces *less* than the predicted amount of output in any given year has a lower than average productivity for that year. Thus, TFP can be interpreted as the relative productivity rank of a plant within its industry in any given year. A *positive* TFP implies that the plant is *above average* within its industry in that year, while a *negative* TFP implies that the plant is *below average* within its industry in that year. Since these regressions include a constant term, TFP only contains the idiosyncratic part of plant productivity.[20] Plant level TFP measures are then aggregated to the firm level by a value weighted approach, where the weights on the plants is the ratio of its output (total value of shipments) to the total output of the firm.[21] The firm level TFP is then winsorized at the 1st and 99th percentile. Schoar (2002), provides an explanation of the relationship between TFP and profits. Holding input costs constant, a certain percentage of higher productivity translates to an equal percentage of increase in revenues, *ceteris paribus*. An increase in revenues leads to a more than proportional increase in profits, since the elasticity of profits to productivity is greater than one. Intuitively, an increase in

[20] As a robustness check for our regression results we use an alternative measure of productivity; valued added per worker, which is defined as total sales less materials cost of goods sold, divided by the number of workers. This measure has been used in McGuckin and Nguyen (1995). This measure does not have the desirable theoretical properties of TFP, but does have familiar statistical properties, since it is not computed from a regression. We find qualitatively similar results when using this measure of labor productivity.

[21] As a robustness check, we also used the ratio of its capital stock to the total capital stock of the firm and the ratio of plant employment to firm employment as weights. In all cases our results remain qualitatively unchanged.

productivity holding all else constant leads to higher revenues without changing costs. Since profits are revenues minus costs, the smaller the profit margin, the higher the elasticity of profits to productivity.

3.2 Other Measures

In this subsection we discuss the construction and measurement of the different firm specific variables as well as other proxies used in our analysis. The LRD data contains detailed information at the plant level on the various production function parameters, such as total value of shipment, employment, labor costs, material costs, new capital investment for the purchase of buildings, machinery, equipment etc. Using this detailed information, we first construct the variables of interest at the plant level, and then aggregate the plant level information to firm level measures.

Capital stock is constructed via the perpetual inventory method, discussed earlier in section 2.1. We measure *Firm Age* as the natural logarithm of one plus the number of years since the first plant of the firm first appeared in the LRD.[22] *Sales* is defined as the total value of shipment in thousands of dollars. *Capital Expenditure* is the dollar value the firm spends on the purchase and maintenance of plant, machinery, and equipment, etc. *Material Cost* is the expense for the cost of materials and parts purchased, resales, contract work, and fuel and energy purchased. *Rental and Administrative Expenditure* is the rental payments or equivalent charges made during the year for the use of buildings, structures, and various office equipment. *Total Wage* is the total production worker wages plus total non-production worker wages plus total supplemental labor costs, which include both legally required supplemental labor costs as well as voluntary supplemental labor costs of the firms. *Total Production Cost* is calculated as the sum of Materials Cost plus Rental and Administrative Expenditures plus Total Wage. All the dollar values in the LRD are in thousands of dollars (in 1998 real terms) and all the plant level measures are winsorized at the 1st and 99th percentile.

We define *Firm Size* as the natural logarithm of capital stock of the firm. *Market Share* is defined as the firm's market share in terms of sales at the annual 3 digit SIC level. We use the market share of the firm to proxy for the firm's industry leader position. We construct the industry *Herfindahl Index* based

[22] In order to properly construct the age variable for plants we start from the Census of 1962, which is the first year for which data is available from the Census Bureau. For plants which started prior to 1962, we use 1962 as the first year for that plant. The age of the firm is then set equal to the age of the first plant of the firm. Given the sampling scheme and scope of LRD, this measure is highly correlated with the actual age of the firm, which we can verify for our sample of VC backed firms, since we are able to obtain the founding date of the VC backed firms from SDC. Particularly, the relative age between venture and non-venture backed firms, which is more relevant for our analysis, is captured very well by this measure.

on the market share measure of each firm in the LRD. The Herfindahl index is calculated by summing up the square of each firm's market share (in sales) at the annual 3 digit SIC level. A higher Herfindahl index means that the industry is more concentrated. *Industry Risk* is defined as the standard-deviation of total firm sales calculated over the prior five year period in the same 3 digit SIC industry. We define *High Tech Firms* as firms belonging to the following 3 digit SIC codes: 357, 366, 367, 372, 381, 382, and 384. We also control for the *Number of Plants* in a firm defined as the number of plants belonging to firm in that particular year. In order to control for overall equity market conditions, we use *S&P 500 Returns* which is defined as the annual return on the Standard & Poor's 500 Index.

In each year, we define VC reputation using the market share of the amount of funds raised by the VC over the prior five year rolling window, following Megginson and Weiss (1991). We think this measure accurately captures VC reputation, since reputation is primarily built on past success and VCs will be able to raise greater follow-on funds only if the performance of their prior existing funds have been successful. This is because, limited partners will be more willing to invest money when a fund has been more successful in the past. In a recent paper, Hochberg, Ljungqvist, and Vissing-Jorgensen (2008) provide direct empirical evidence showing that both the probability of raising a follow-on fund and the size of the follow-on fund increases in the return that investors earned in the previous fund of the same VC, thus suggesting that more successful VCs are able to raise larger follow-on investments.[23] For each VC-backed firm in our sample, we then calculate the average reputation of the VC syndicate that provides the first round of VC financing to that firm. *High Reputation* corresponds to the average market share of funds raised by the VC syndicate being above the sample median, while *Low Reputation* corresponds to the average market share of funds raised being below the sample median.[24] For robustness, we also use an alternative measure of VC reputation based on the market share of the total amount of investment made by the VC firm over a five year rolling window and the market share of the market capitalization of IPO exits (on the first trading day) of the VC's portfolio firms over a five year rolling window.[25]

In addition to the firm specific and industry wide controls mentioned above, we also use several

[23] Our reputation measure based on the market share of the amount of funds raised by a VC is also quite persistent over time. This is consistent with the evidence in Kaplan and Schoar (2005) and Hochberg, Ljungqvist, and Vissing-Jorgensen (2008) showing persistence in fund performance.

[24] Such a market share based measure may also reflect VC expertise or VC experience in addition to prior success of the VC as measured by internal rates of return. For the purposes of this paper, we use the words reputation (which is built on prior success) and experience or expertise interchangeably.

[25] We also recalculate our reputation measures by allowing the market shares to be calculated over the entire life of the VC firm as opposed to the last five years. All our results remain qualitatively unchanged to these alternative definitions of VC reputation.

variables as instruments in our switching regression analysis (that we discuss in detail below). The primary instruments we use to capture the potential demand for VC funds from entrepreneurial firms relate to the increase in National Science Foundation (NSF) grants (in real terms) to Applied and Basic research.[26] Our intuition is that an increase in *NSF Research Grants* could lead to an increase in the establishment of new entrepreneurial firms that may then potentially seek VC investment. To identify the potential supply of VC funds we use the number of limited partners (LPs), defined as the total number of limited partners investing in VC funds that exist over the previous five years. Using a similar logic, we also use the fraction of the number of LPs in the past five years that are located in the state of the company to capture the potential heterogeneity in the supply of entrepreneurial funds. The greater the availability of LPs and the more of the LPs that are in geographic proximity to the company, the greater should be the ability of local VCs to raise financing and thus, the greater should be the reputation of the VC firm. In addition, the *AAA Spread*, which is the spread of AAA bonds over five year Treasury bonds, captures the investment alternatives available to investors that may invest in VC funds. An increase in the spread may lead to a decline in commitments to VC funds thus lowering overall VC investments. We discuss the significance of using these instruments for our analysis later on in the paper.

4 Do Venture Capitalists Improve Firm Efficiency?

4.1 Descriptive Statistics

As mentioned earlier, the sample of VC-backed firms used in this study comprises all private firms in the LRD that received VC funding between the years 1972 and 2000. In order to benchmark the effect of VC financing properly, we also include in our sample all private firms in the LRD that did not receive VC financing. Panel A of Table 2 presents the summary statistics (means and quasi-medians) of firm characteristics for both VC-backed and non-VC-backed private firms in the LRD during our sample period.[27] We find that VC financed firms in our sample are on average larger than non-VC financed

[26] *NSF Basic Research Grants* are defined as "systematic study directed toward fuller knowledge or understanding of the fundamental aspects of phenomena and of observable facts without specific applications toward processes or products in mind", while *NSF Applied Research Grants* are defined as "systematic study to gain knowledge or understanding necessary to determine the means by which a recognized and specific need may be met". Further details can be found on the NSF website at: http://www.nsf.gov/statistics/nsf07303/content.cfm?pub_id=3734&id=1

[27] In order to comply with the confidentiality criteria of the U.S. Census Bureau, we are unable to report the medians of firm characteristics. Therefore, to circumvent this problem, we report quasi-medians, which are the average of the 43rd and the 57th percentile of each variable and closely approximates the true median value of the variables.

firms, in terms of asset value, sales, and total employment. Based on asset value, VC-backed firms are on average 7 times larger than that of non-VC-backed firms, while the average sales of VC-backed firms is about 6 times larger than that of non-VC-backed firms. Total cost of materials and total salaries and wages for VC-backed firms is also larger (on average about 5.5 times) than that of non-VC-backed firms, consistent with the argument made by Puri and Zarutskie (2009) regarding the importance of scale in VC financing. In addition, as suggested by anecdotal evidence and several prior papers, we also find that a greater proportion of high tech firms are VC financed. We find that VCs on average invest in industries that have a higher volatility of firm sales over the last 5 years, suggesting that VCs tend to invest more in industries that are inherently riskier and thus the potential contribution that the VC can make to the ultimate success of firms in such an industry is also significantly greater. Finally, we show that the median age at which firms receive their first round of VC financing is at 3 years.

In order to address the potentially unbalanced nature of the LRD sample, in Panel B of Table 2, we present further summary statistics for our VC-backed sample of firms. Specifically, we look at VC-backed firms that received their first round of VC financing in census years (i.e., in the years 1972, 1977, 1982, 1987, 1992, and 1997) and compare them to VC-backed firms that received their first round of financing in all other non-census years. The intuition for this test is as follows: since the entire universe of manufacturing plants are included in census years, the average VC-backed firm in these years would be significantly smaller in size if indeed there is a significant discrepancy in the coverage of smaller VC-backed firms in non-census years. If it were so, one could argue that we are unable to identify smaller VC-backed firms in non-census years. The results of Panel B, however, rule out this concern, since we find that firms that receive VC financing in census years are not smaller than firms that receive VC financing in non–census years. We use various measures for size such as total assets, total sales, total employment, total salaries and wages, market share, etc. and do not find any statistically significant difference between the size of firms receiving VC financing in census years and the size of firms receiving VC financing in non-census years. This result thus provides support to the fact that our analysis uses a representative sample of VC-backed firms within the manufacturing sector and that our results are not driven by the presence of larger VC-backed firms in our sample.

4.2 The Impact of Venture Capital Financing on Firm TFP

4.2.1 Impact of Screening and Monitoring: Differences in TFP dynamics around the first year of VC Financing

In our subsequent analysis we use total factor productivity (TFP) as a comprehensive index of firm efficiency.[28] First, we analyze the productivity of VC-backed firms relative to that of non-VC-backed firms. Second, we document the dynamic pattern of productivity changes from *before* to *after* the first round of VC financing, benchmarked against firms not receiving VC financing and attempt to disentangle the impact on TFP arising due to VC *screening* prior to funding from that arising due to *monitoring* activities of VCs subsequent to funding.[29] We employ a regression framework to analyze these effects, where we include firm and year fixed effects which allow us to precisely control for differences between firms and across time, respectively. This helps us to isolate the impact of screening on post-financing TFP to a certain extent. In addition, as VC financing of firms are distributed over time, we allow for the staggering of the events in our regressions. Finally, we control for time varying observables of the firm and industry. The methodology adopted in our regression framework throughout this paper is consistent with that suggested by Petersen (2009), who advocates using fixed effects and adjusting the standard errors for correlations within clusters. In all regressions we include firm and year fixed effects and report standard errors clustered at the firm level. We implement this approach through the following regressions:

$$Y_{it} = \alpha_t + \beta_i + \gamma X_{it} + \delta VCAfter_{it} + \varepsilon_{it} \tag{2}$$

$$Y_{it} = \alpha_t + \beta_i + \gamma X_{it} + \delta_1 VCBefore_{-4,0} + \delta_2 VCAfter_{1,4} + \delta_3 VCAfter_{\geq 5} + \varepsilon_{it} \tag{3}$$

[28] It is important to note that since TFP is computed from the residuals of four-digit SIC-year regressions, which includes factors that determine the scale of production in the firm as independent variables, the residual (i.e., TFP) is independent of scale of production. Thus, this measure is particularly suited to examine the contributions made by VCs, since it captures efficiency changes that are independent of the scale of production. This is especially important in light of our summary statistics and that of other studies that highlight the importance of scale in VC financing.

[29] It should be noted that it is not possible for us to differentiate between the effect of monitoring and contracting on firm TFP. Thus, in this paper we combine these two effects and for simplicity refer to it as monitoring. It can be argued that the level of monitoring and the stringency of the financial contract are simultaneously determined, since the VC can trade-off one for the other. Ultimately, what is important for our analysis is the relative improvement in efficiency that VC firms achieve over non-VC firms subsequent to receiving VC financing and the fact that this improvement in performance and efficiency can be attributed to the involvement of the VC with these firms.

$$Y_{it} = \alpha_t + \beta_i + \gamma X_{it} + \sum_{s=0}^{-4} \delta_1^s VCBefore_{it}^s + \sum_{s=1}^{\geq 5} \delta_2^s VCAfter_{it}^s + \varepsilon_{it} \tag{4}$$

where Y_{it} is our variable of interest, i.e., firm TFP; X_{it} is a control for firm size and the industry Herfindahl index which are time varying; $VCAfter_{it}$ in (2) is a dummy variable, which equals 1 if the firm received VC financing and the observation is in a year after the first round of financing and 0 if it is a firm that either did not receive VC financing or is a VC-backed firm, but with the observation belonging to a year prior to the first round of VC financing.[30] In (3), we introduce $VCBefore_{-4,0}$, which is a dummy variable that equals 1 if the firm received VC financing and the observation is within five years prior to the first round of financing and 0 otherwise. Conceptually, this variable is similar to the $VCAfter_{it}$ variable and captures the difference in the TFP between VC-backed and non-VC-backed firms in the years prior to receiving VC financing. We also decompose the $VCAfter_{it}$ variable into two parts: $VCAfter_{1,4}$ captures the changes from years 1 to 4 subsequent to the first round of financing and $VCAfter_{\geq 5}$ captures the effect on TFP from the 5th year after the first round of financing till exit. This allows us to address how the changes brought about by the VC financing are distributed over time around the first year of receiving VC financing. In order to shed more light on the year by year changes in firm TFP due to VC financing, we estimate (4), where we decompose both the $VCBefore_{it}$ and $VCAfter_{it}$ dummies separately for each year. For example, $VCAfter_{it}^s$ equals 1 if the firm receives VC financing and the observation is s years after the first round of financing, where $s = 1, 2, 3, 4,$and ≥ 5.[31] The dynamic pattern of the effect of VC financing on TFP is captured by the coefficients $\delta's$ in all three equations. In all specifications i indexes firms, t indexes years, β_i are firm fixed effects and α_t are year fixed effects. The above specifications are estimated on the entire panel of private firms in the LRD including firms that received VC funding and those that did not. It should however be noted, that the above fixed effects methodology may not properly capture the screening and monitoring effects of VC-backing, if VCs have private information about the firms they invest in and particularly if such information is correlated with future TFP increases. We therefore use two alternative methodologies later on to provide a causal impact on TFP growth due to the monitoring

[30] This variable is conceptually similar to the interaction of two dummy variables $VC * After$ where VC is a dummy variable which equals 1 if the firm receives VC financing and 0 otherwise, and $After$ is a dummy variable which equals 1 if the observation is in a year following the first round of VC financing and 0 otherwise. Note that $After$ is always 0 for non-VC backed firms. Thus, this specification implicitly takes all firms that have not received VC financing prior to time t as the control group.

[31] The $VCBefore_{it}^s$ dummy is simiarly defined. Specifically, $VCBefore_{it}^0$ refers to a firm that received VC backing with the observation in the year it received the first round of VC financing, and $VCBefore_{it}^1$ refers to a VC backed firm one year before receiving the first round of financing, and so on.

activities of VCs.

Panel A of Table 3 presents the results which shows the effect of VC monitoring and screening on firm TFP. Our estimate of the effect of VC monitoring on a firm's TFP is captured by the $\delta_2's$, the coefficients on $VCAfter$ and the effect of VC screening on a firm's TFP is captured by the $\delta_1's$, the coefficients on $VCBefore$.[32] As can be seen from Table 3, VCs actively engage in both screening and monitoring.[33] *Regression 2* and *Regression 3* in Panel A of Table 3 shows that, on average, firms financed by VCs have 7% higher TFP over the 5 years prior to receiving funding, compared to firms that do not obtain VC financing, indicating that VCs actively screen firms prior to funding and select the ones with higher levels of productivity.[34] Furthermore, subsequent to funding, TFP of VC-backed firms improves even further, on average to 12% over the next 4 years, over and above that of non-VC-backed firms, suggesting that VCs actively monitor their investments and improve the performance and efficiency of firms they fund. Finally, *Regression 4* decomposes the screening and monitoring effects dynamically for every year around the first round of VC funding. As can be seen from the results, for every year prior to receiving funding, VC-backed firms outperform non-VC-backed firms. While there is no apparent trend over the years prior to receiving funding, on average these firms had higher TFP of around 7% relative to non-VC firms, similar to the earlier results. After receiving funding, we observe an increasing trend of TFP for VC-backed firms for 5 years after the first round of financing, suggesting that the involvement of VCs and their monitoring of these firms leads to an increase in the TFP of these firms over and above that of non-VC-backed firms. This increase is more pronounced after 5 years (and beyond) of receiving funding

[32] These results give us an indication of how screening and monitoring activities of VC's impact firm performance and efficiency as measured by TFP. However, as one might argue, these coefficients could potentially be confounded due to an endogeneity problem that arises between VC financing and changes in firm TFP due to selection. We explore this in more detail later and employ an endogenous switching regression methodology as well as the propensity score matching methodology to accurately capture the relative magnitudes of the impact of screening and monitoring on firm TFP. The results from that procedure are presented in Tables 6, 7, and 8. However, the qualitative results obtained from this table remain unchanged even after correcting the potential endogeneity issue.

[33] Our results are broadly consistent with the evidence presented in Sorensen (2007). While we analyze the productivity of VC backed firms at the time of financing, Sorensen's analysis uses only IPO exits as a measure of performance. Sorensen (2007) distinguishes between sorting and influence and their impact on the probability of an IPO. Even though the above two concepts are similar to the screening and monitoring effects of VC financing that we analyze here, there are important differences. One such difference is that sorting refers to a double sided matching between VC's and entrepreneurial firms, whereby more experienced VC's are paired with better quality firms. This mechanism inherently assumes that there is full information available to both parties about each other. Screening, on the other hand refers to the VC's ability to select better performing firms based on their private information, in the presence of information asymmetry.

[34] As explained in section 2.1, TFP can be thought of as the relative rank of a firm within it's four digit SIC industry in a particular year. Thus, TFP is not directly observable, it can only be estimated if one has complete information about all public and private firms in an industry in any given year. Thus, it can be argued that TFP of a firm reflects unobservable information. It thus seems that at the time of providing financing, VC's may know more than what is directly observable in the data.

when the TFP for VC-backed firms increases to about 19% above that of non-VC-backed firms. In almost all cases, the coefficients of interest in *Regression 1* to *Regression 4* are significant at the 1% level.

Panel B of Table 3 presents the net effect on firm TFP that can be attributed to the monitoring abilities of VCs. Based on *Regression 2* to *Regression 4*, we find that the average increase in TFP from before receiving VC financing to 4 years after receiving VC financing is around 5% to 8% for VC-backed firms. This increase is around 12% for VC-backed firms when we compute the difference in TFP after year 5. In *Regression 4*, we compute the net effect of monitoring year by year for VC-backed firms relative to the year prior to receiving financing. Consistent with the evidence presented so far, we observe that there is a monotonically increasing effect of VC monitoring on TFP. In the 2 years after the first financing round, the impact of monitoring is around 5.5%, which monotonically increases to around 14% after the 5th year subsequent to the first round of financing.[35] Overall, the results from Panels A and B of Table 3 suggest that VCs actively engage in both screening and monitoring. On average, we find that due to their screening ability, VCs invest in firms that have around 6% higher TFP than firms that do not receive VC funding. We also find that the net effect of monitoring on the TFP of firms is between 5.5% to around 14%. Thus, our results suggest that the impact of screening and monitoring of VCs on firm performance and efficiency are both important and on average they have similar magnitudes, if we solely consider the net effect of monitoring during the first two years after receiving the first round of financing. The results presented here are also economically highly significant. The higher TFP of 6% in VC-backed firms due to screening, and the increase in net average TFP of 10% due to monitoring of VCs translate to an increase in profits of approximately 21% and 35%, respectively.[36]

The above results are consistent with prior papers in the literature that argue that VCs create value through screening and monitoring, such as Lerner (1995) and Hellmann and Puri (2000, 2002). Our results complement these earlier studies and present direct evidence regarding the impact of such activities of VCs

[35] It should be noted however, that this entire net effect of monitoring on firm TFP should not only be attributed to the first round of VC financing. Since there are typically multiple rounds of financing that a VC backed firm receives, the net impact of monitoring that we find here could potentially be attributed to multiple rounds of financing. As mentioned earlier, our TFP measure is independent of the scale of production; so while this net increase in TFP is not due to the direct effect of capital infusion of the later rounds, it could potentially be argued that the level of monitoring of a VC could increase with the amount of investment made in the firm. Thus, this could lead us to observe the net higher increase in TFP for the years that are further away from the initial year of investment. We analyze this in the next subsection, when we look at TFP improvements around subsequent rounds of VC financing.

[36] Schoar (2002), provides an explanation of the relation between TFP and profits. Holding input costs constant, a certain percentage of higher productivity translates to an equal percentage of increase in revenues, *ceteris paribus*. Therefore, the elasticity of profits to productivity is greater than one and the smaller the profit margin, the higher the elasticity of profits to productivity. The 21% and 35% annual increase in profits are calculated based on the assumption of a revenue margin of 40% over costs, *ceteris paribus*.

on firm performance and efficiency over and above that of non-VC-backed private firms. In particular, this is the first study to directly relate the productivity levels in VC-backed firms to that of non-VC-backed firms both prior to and after receiving VC financing, thus quantifying the impact on firm TFP due to VC involvement.

4.2.2 TFP Dynamics for Early and Late Stage Venture Capital Backed Firms

A potential concern is that our sample of manufacturing VC-backed firms may be somewhat biased toward later stage VC-backed firms, and thus our results may not be generalizable to early stage firms.[37] To address this concern, we run our fixed effect regressions separately on the set of early and late stage VC-backed firms. Early stage firms are firms whose stage at the first round of VC financing is described in SDC *VentureXpert* as "Early stage" or "Seed/Startup." Table 4 reports the results of the fixed effects regressions for the set of early and late stage VC-backed firms. We find that the results for the set of early and late stage VC-backed firms are similar to the regression results for the overall sample. Further, the monitoring impact of venture capitalists is stronger for the set of early stage VC-backed firms: the increase in TFP over the five years after receiving VC financing from the five years prior to receiving VC financing is statistically significant only for the sample of early stage VC-backed firms. Further, the economic magnitudes of TFP increases from before to after VC financing is greater for the set of early stage VC-backed firms.

These results are consistent with our overall results in the previous section, and thus they mitigate concerns that our results are driven by late stage VC-backed firms. Rather, the economic effect of VC monitoring on firm TFP is greater for the sample for early stage VC-backed firms.[38]

4.2.3 The Effect of Option Compensation on TFP Dynamics

Hellmann and Puri (2002) argue that in order to increase incentives, VC's may introduce option based compensation to firm management at the time of providing financing. Thus, a potential concern with our above results is that our TFP calculations understate the magnitude of option compensation, which in turn

[37] Approximately 42% of our sample consists of early-stage VC-backed firms.

[38] We also repeat this analysis by splitting our sample into young and old VC-backed firms, based on firm age at VC financing. Our results are similar to the ones reported in the paper: We find that TFP is greater prior to VC financing and increases even more subsequent to VC financing for both younger and older firms. The monitoring effect seems to be stronger for younger VC-backed firms.

might mechanically bias our TFP measure upwards.[39] To alleviate this concern, we perform an adjustment to our TFP measure. Using aggregate industry level option compensation data, we adjust the labor input in the Cobb-Douglas production function to reflect the greater expense of providing option compensation. In particular, we adjust the salaries and wages of white collar employees in VC-backed firms, from the year in which they receive VC financing, upwards by a factor which is equal to one plus the ratio of average options to cash compensation in the same year and 3-digit SIC industry as for the VC-backed firm. We do not adjust the labor input for the non-VC-backed firms or for VC-backed firms in the years prior to receiving VC financing. We then run our TFP regressions using this adjusted labor input measure and calculate firm level TFP as before.

We obtain data on the stock options and compensation from the *Execucomp* database. Since this database only provides data from 1992, we make two different assumptions about the options adjustment prior to 1992. In the first adjustment, we fix all option compensation level prior to 1992 at the 1992 level. This is a potentially conservative adjustment (i.e., it lowers the TFP much more) because prior literature (e.g., Frydman and Saks (2010)) suggests that options compensation levels has been steadily increasing over the 1980s and the 1990s. In the second adjustment, we calculate the average annual compounded growth rate of options in the years after 1992, and use this growth rate to decrease the option compensation adjustment backwards from 1992.[40]

Our results, reported in Table 5, indicate that even after adjusting for options in this way our results remain qualitatively similar.[41] In particular, we find that VC-backed firms have higher option-adjusted TFP than non-VC-backed firms prior to the VC financing, and this option-adjusted TFP increases subsequent to investment by the VC. Our results hold for both types of pre-1992 option adjustment methods. Thus, the results in this section mitigate concerns that our results may be driven by overstatement of the TFP due to not adjusting our labor measure appropriately for the introduction of option compensation in VC-backed firms.

[39] We are grateful to an anonymous referee for his suggestions on adjustment of the labor measure for option compensation.

[40] In particular, we calculate the average growth rate for each 3-digit SIC industry as $g = ((1+g_1)(1+g_2)...(1+g_n))^{1/n} - 1$.Then, we adjust options to cash compensation ratio backward as $opt/comp_{t-1} = (opt/comp_t)/(1+g)$. In unreported tests, we also use data from Frydman and Saks (2010) to directly compute the adjustment ratio for the labor input for all years in our sample and use that to compute our TFP measure. We thank Carola Frydman for generously providing us with her data to make this possible.

[41] Our results are also qualitatively similar when we use data only after 1992 for the fixed effects regressions.

4.2.4 Impact of Screening and Monitoring: Differences in TFP dynamics around VC Financing Rounds

In this section, we analyze the above dynamics in TFP changes round by round for VC-backed firms to see how the TFP improvements documented above may be spread over different rounds of venture financing received by the firm. We do this by estimating a modified version of (3) where we replace the $VCAfter$ dummies by $VCAfterRound$ dummies. Specifically, we look at TFP improvements after *Round 1*, *Round 2*, *Round 3*, and *Round 4* or greater. The results are presented in Table 6. The round by round results, reported in Panel A of Table 6, are consistent with those discussed in the previous section and show that at each round after receiving financing and in the years prior to receiving VC financing, the TFP of VC-backed firms is significantly greater than the TFP of non-VC-backed firms.

In Panel B of Table 6, we show that the TFP for VC-backed firms after each round is significantly greater than the TFP of the firms prior to receiving VC financing. Additionally, the TFP in *Round 2* (i.e., between round 2 and 3) is significantly greater than the TFP in *Round 1* (i.e., between round 1 and 2), suggesting a monotonic increase in TFP from round 1 till end of round 2 for VC-backed firms. While the TFP improvement after *Round 1* and before *Round 2* is around 5%, the TFP improvement after *Round 2* and before *Round 3* is significantly greater at 9%. However, TFP after *Round 3* are not significantly greater than the TFP before that round. This result therefore suggests that increases in TFP for VC-backed firms is achieved within the first couple of rounds of VC involvement with the firm.

4.3 Effect of Monitoring on TFP: Switching Regressions with Endogenous Switching

In this section, we present further evidence on the impact of monitoring by VCs on firm TFP and efficiency. Our results from the previous section suggest that VCs screen firms and thus the VC-firm matching may be nonrandom. As such, this matching potentially confounds the effects of VC monitoring on firm performance with the effects arising due to the screening and/or the firm characteristics on subsequent performance. In other words, the selection or matching between the VC and the firm that receives financing is potentially endogenous with subsequent firm performance. Thus, to disentangle the monitoring effect, we are interested in the following "what-if" type of questions: For a firm financed by a VC, what would the alternative future performance have been *had it not received* VC financing? Similarly, for a firm that did not receive VC financing, what would the alternative future performance have been *had it received* VC

financing? The answer to these questions holds the impact of screening on TFP constant and separates out the effect of monitoring on firm TFP due to VC financing.

To implement this, we adopt a two-step Heckman-type estimation structure and employ switching regressions with endogenous switching to disentangle the impact of screening and monitoring on TFP of VC-backed firms. This procedure is discussed in detail in Heckman (1979) and Maddala (1983) and is a generalized version of the traditional Heckman model and therefore accounts for the effect of unobservables or private information by using the inverse Mill's ratio in the second stage of the estimation. This model appears in Lee (1978) in his study of unionism and wage rates, Dunbar (1995) in his study of the use of warrants as underwriter compensation, and more recently in Fang (2005) in her study on investment bank reputation and the price and quality of bond underwriting services provided by them. Please see the technical appendix for further details on this methodology.

We control for firm-level characteristics that could affect the VC-firm matching, such as the average five year prior TFP, firm size, the number of plants operated by the firm, firm age, market share, and whether the firm operates in a high tech industry or not; industry level characteristics such as the industry Herfindahl index and the riskiness of the industry in which the firm operates; market wide characteristics such as the *S&P500* return, and time dummies capturing the 80s, the 90s, and the internet-bubble period. In addition, we also include several instruments that are correlated with the demand and supply of venture funds in the economy but are independent of the future performance of VC-backed firms; namely, the increase in NSF applied research grants, the increase in NSF basic research grants, the total number of LPs, the fraction of total LPs in the same state as the company, and the AAA spread. These instruments provide us with exogenous variation both in terms of supply of, and demand for, VC funds which affects the selection equation (i.e., the matching outcome) but do not directly affect the impact on firm performance due to VC monitoring.

The results of the switching regression analysis, reported in Table 7, show that prior average TFP, firm size, number of plants operated by the firm, herfindahl index, and the high tech dummy are all positive and significant determinants of receiving VC financing. Firm age and industry risk are negative and significant determinants of VC financing. With regard to the instruments, we find that the coefficient on the increase in NSF applied research grants is positive and significant, while the coefficient on the increase in NSF basic research grant is negative, suggesting that greater applied research may lead to an increase in entrepreneurial firm formation, thus leading to greater demand for VC funds. Similarly, the

coefficients on the number of LPs and the fraction of instate LPs are also positive and significant suggesting a greater probability of receiving VC funding in the presence of a greater number of LPs. As expected, the coefficient on AAA spread is negative and significant, suggesting that availability of funds to VCs is an important criterion for VC financing, consistent with Gompers and Lerner (1998). We then augment the second stage regressions for VC-backed and non-VC-backed firms with the inverse Mills ratio calculated from the first stage to account for the endogenous selection.

The second stage results show that, while the inverse Mills ratio is positive and significant for VC-backed firms, it is insignificant for non-VC-backed firms. This suggests that VCs have private information about the firms that they select to invest in, and this private information (that they condition the selection on) positively affects the future TFP growth of firms receiving VC financing. Therefore, properly controlling for this effect enables us to attribute the residual TFP growth of VC-backed firms to the monitoring activities of VCs. We find that lower average prior TFP leads to higher future TFP growth in both VC and non-VC-backed firms. While larger firms have higher future TFP growth among VC-backed firms, smaller firms, multi-plant firms, younger firms, and firms with greater market share have higher future TFP growth among non-VC-backed firms.

Table 8 presents the results for of our counterfactual analysis of VC-backed versus non-VC-backed firms. We generate the counterfactual values of TFP growth by using the predicted values of the non-VC backed regression and implied inverse mills ratio for VC backed firms, and vice versa. These results suggest that, on average, VC-backed firms achieve a TFP growth of approximately 18.5% higher than what the *same firms* would have achieved had they not received VC financing, suggesting a monitoring effect. The second row shows the hypothetical improvement in TFP growth of 4.3% for non-VC-backed firms had the *same firms* received VC financing. The magnitude of this improvement attributed to monitoring is consistent with our earlier results presented in Table 3 and is also both statistically and economically significant, since it corresponds to a 40% increase in profits after receiving VC financing.

In summary, these results empirically show the impact of monitoring on firm efficiency and productivity. We explicitly account for the endogenous nature of the VC-firm selection process using a Heckman style two-stage model and after controlling for this selection, we find VCs have a significant positive monitoring effect on the post-financing TFP of the firms that they invest in.

4.4 Effect of Monitoring on TFP: Regression Discontinuity Analysis

In this section, we demonstrate the causal effect of venture capitalists on the productivity of the firms they invest in (i.e., monitoring) using a regression discontinuity (RD) approach. Specifically, we use the "fuzzy" RD technique discussed in Angrist and Lavy (1999) and Van Der Klaauw (2002).[42] Identification in a fuzzy RD technique comes from a discontinuous jump in the probability of treatment. We use a two-stage approach similar to the ones used in the above papers to implement our RD analysis. Our estimation equation is:

$$y_j = x_j\beta + \delta I_j + \varepsilon_j \tag{5}$$

where, y_j is the growth in the productivity of the firm, I_j is the endogenous treatment variable which in our case is a dummy equal to 1 for VC-backed firms in the year they obtain VC financing, and 0 otherwise, and x_j is a set of control variables. The fuzzy RD approach requires an assignment variable S_j such that $\Pr(I_j|S_j)$ experiences a jump at a known point $S_j = S_0$. Note that, unlike the endogenous switching regression approach used earlier, S_j can be correlated with the test variable y_j. The restriction required for identification is that no other effect causes a jump in y_j at $S_j = S_0$. The regression discontinuity can be implemented with a two stage approach. We first estimate:

$$\Pr(I_j|S_j) = \phi.S_j + \gamma.1.\{S_j \geq S_0\} + \eta_j \tag{6}$$

where, $1\{S_j \geq S_0\}$ is an indicator function that equals 1 if $S_j \geq S_0$ and 0 otherwise, and η_j is the error term. We augment the second stage equation with $\Pr(I_j|S_j)$, which is calculated as the predicted probability from (6). The second stage model is estimated as:

$$y_j = x_j\beta + \delta \Pr(I_j|S_j) + \rho S_j + u_j \tag{7}$$

This approach is analogous to a two stage least squares approach, with the discontinuity $1.\{S_j \geq S_0\}$ serving as the identifying instrument.[43]

[42] See also Frandsen (2008) and Hahn, Todd, Van Der Klaauw (2001) for detailed discussions of the regression discontinuity design.

[43] The standard errors in the second stage are bootstrapped to account for generated regressors. We also conduct the above analysis in a two stage least squares framework rather than estimating the first stage as a probit regression. In addition, we estimate a panel data two stage least squares model with firm fixed effects. Our results do not qualitatively change in the

To obtain the discontinuity to identify our system, we exploit the fact that the US Small Business Administration (SBA) provides financial support to firms upto a certain size cutoff.[44] For most industrial firms, the size cutoff is a pre-specified level of employment that varies with the NAICS industry affiliation of the firm.[45] Our assignment variable, S_j, is the normalized level of employment in the firm, i.e.,

$$S_j = Normalized\ Employment\ = \frac{Firm\ Employment}{Employment\ Cutoff\ for\ SBA\ Support\ Eligibility}$$

Thus, we expect a discontinuity in the propensity of firms to seek and obtain VC financing at $S_j = 1$. At all points below $S_j = 1$, firms are eligible for SBA support and therefore have a viable alternative to VC financing and are thus less likely to seek and obtain VC financing. At points above $S_j = 1$, firms are not eligible for SBA support, and as a result are more likely to seek and obtain VC financing.

We start by showing a graphical analysis of the discontinuity. Figure 1 graphs a kernel weighted mean smoothing estimator of the propensity to obtain VC financing as a function of our assignment variable. The graph clearly indicates that there is indeed a jump in the propensity to obtain VC financing at the point where normalized employment equals one, as expected.

One concern with the assignment variable may be that firms may try to obtain federal funding by artificially restricting their size levels to comply with SBA requirements. McCrary (2008) argues that such active sorting may undermine the identification requirements of the regression discontinuity design. To rule out this concern, we graphically and statistically analyze the density function of the normalized employment variable around the cutoff point (i.e., at $S_j = 1$). Visual analysis of the graph indicates a smooth density function of S_j at the cutoff point. We then conduct the statistical test recommended in McCrary (2008) to ensure that our identification strategy is valid. The test is implemented as a Wald test of the null hypothesis that the discontinuity in the density function of the assignment variable is zero at the cutoff point. The test does not find a statistically significant jump or drop in the density function of

above specifications.

[44] The SBA provides a number of financial assistance programs for small businesses including equity financing, debt financing through guarantees to commercial lenders to provide funding to small firms, and surety bond guarantees to help small businesses obtain contracts. In 2006, the total value of financial support provided by the SBA to small businesses was $78.1 billion, which grew to $90.45 billion in 2009, indicating that the SBA represents a significant source of financial support for smaller entrepreneurial firms. See http://www.sba.gov/idc/groups/public/documents/sba_homepage/serv_abtsba_2009_afr_001-030.pdf (Page 7).

[45] Size eligibility standards to receive SBA financial support are listed at the SBA website: http://www.sba.gov/idc/groups/public/documents/sba_homepage/serv_sstd_tablepdf.pdf

the assignment variable S_j at the cutoff point, i.e., $S_j = 1$, thereby validating our identification strategy.[46]

The results of the two-stage RD analysis are reported in Table 9. Consistent with our expectations, the coefficient estimate on the jump indicator (i.e., $Indicator(Norm.Emp. > 1)$) is statistically significant and positive in the first stage regression, indicating that there is a jump in the propensity to obtain VC financing at the point where a firm outgrows its eligibility for SBA support. In the second stage, we find that the coefficient estimate on the predicted probability of VC financing from the first stage is positive and statistically significant. Thus, after controlling for the selection of firms by VCs using the regression discontinuity approach, we find that VC financing leads to higher levels of productivity growth. Our results are therefore consistent with the notion that VC monitoring leads to an increase in firm productivity.

4.5 Effect of Monitoring on TFP: Propensity Score Matching

In this section, as an additional robustness check, we employ yet another methodology to confirm our earlier results on the effect of VC monitoring on subsequent growth in firm TFP. We employ a propensity score matching algorithm, where we match firms on multiple dimensions in the year prior to receiving VC financing. Specifically, we require that the matched firm be in the same 3-digit SIC industry as the sample firm, be of similar size, and have a similar level of average prior TFP in the 5 years prior to receiving funding. The last criteria ensures that at the time of receiving VC financing, both our sample (VC-backed firms) and matched (non-VC-backed firms) portfolios have similar levels of productivity and efficiency.

Table 10 presents the results for of the propensity score matching based analysis. By construction, the average five year TFP prior to receiving VC financing is similar and not statistically different between VC-backed and non-VC-backed matching firms. However, when we compare the TFP growth over the next five years for our two portfolios, we observe that while the VC-backed firms realize significantly positive TFP growth (both at the mean and the quasi-median), the matched sample of non-VC-backed firms do not. Moreover, the difference in TFP growth between the two groups of firms is statistically and economically significant, with the mean of the VC-backed firms being approximately 5% higher and the quasi-median being approximately 4% higher than the matched sample of non-VC-backed firms. Consistent with our earlier findings, this result also suggests that VC involvement improves the efficiency of VC-backed firms through the extra-financial monitoring services provided by the VCs, with the magnitude of this effect

[46] The estimator for this test is calculated in two steps. First, one obtains a finely gridded histogram. Second, one smoothes the histogram using local linear regression separately on either side of the cutoff point. The test statistic is based on the estimates of the density function from local linear regressions from the two sides of the cutoff point.

being similar to that documented in the earlier sections.

5 The Channels through which VCs Improve Firm Efficiency

In this section, we identify the channels through which efficiency improvements are realized for VC-backed firms compared to non-VC-backed firms. In order to do this, we investigate the dynamics of firm output as well as the various inputs (capital, materials, and labor) around the years of receiving the first round of VC financing, benchmarked against that of non-VC-backed firms. We implement this using the regression specification outlined in equation (3), where our dependent variables in the various regressions are as identified in the column headings in Table 11. We control for firm size and include both firm and year fixed effects and cluster the standard errors at the firm level. Panel A of Table 11 presents the regression results, while Panel B presents the changes in the dependent variables over time from before receiving VC financing to after receiving VC financing.

As can be seen from the results, sales for VC-backed firms are larger prior to VC financing and increase significantly over time from before receiving financing to after receiving financing as compared to that of non-VC firms. This increase in sales is even more pronounced in years five and after receiving the first round of financing. Similar to this increase in total sales, our results also document increases in total production cost for firms from before receiving VC financing to after receiving financing. This increase in total production cost mainly arises from increases in materials cost. Compared to non-VC-backed firms, total labor cost is greater in VC-backed firms prior to receiving financing, and also increase subsequent to receiving VC financing. While materials cost increases monotonically after receiving VC funding, the increase in labor cost is only evident during the first four years after receiving VC financing; for five years and after VC financing, we do not find a significant difference in the growth of salaries and wages from before receiving financing. We also find no changes in the level of total employment growth from before receiving VC financing to after receiving financing. Finally, we document that while capital expenditure is greater for VC-backed firms prior to receiving financing compared to non-VC-backed firms, there is no significant change in capital expenditure for VC-backed firms from before receiving financing to after receiving financing.

Overall, the results presented in Table 11 suggest that the increase in efficiency of VC-backed firms, that we document, on average come about through the improved product market performance of these

firms (i.e., increases in sales) which may arise through the extra-financial services provided by the VCs. Further, the results are also consistent with the interpretation that VCs may be employing higher quality workers in the years immediately after investing in the firm in order to improve their operating efficiency, as documented previously by Hellmann and Puri (2002).

6 Differences between High and Low Reputation VC-backed Firms

6.1 Differences in TFP dynamics for High and Low Reputation VC-backed firms

Given the choice, entrepreneurs would prefer to source financing from high-reputation VCs rather than from low-reputation VCs. Hsu (2004) points out that a financing offer from a high-reputation VC is approximately three times more likely to be accepted by an entrepreneur and also that high-reputation VCs get better deal terms (i.e., lower valuations) when negotiating with start-ups. This suggests that start-up firms will only be willing to accept such terms if high-reputation VCs provided superior monitoring and management, subsequently leading to better firm performance. In this section our aim is to empirically show this. We thus run our fixed effects regression on the sample of high and low reputation VC-backed firms separately, and estimate the joint covariance matrix for (3) estimated for high and low-reputation VC-backed firms.[47] In Panel A of Table 12, the first two columns correspond to high and low-reputation VC backed firm regressions, respectively; the third column presents the difference in TFPs between high and low-reputation VCs at all stages; and the fourth column presents the difference in the net effect of monitoring (i.e., $TFP_{After} - TFP_{Before}$) between high and low-reputation VCs.

Consistent with our earlier results, we find that both high and low-reputation VCs actively engage in screening and select firms that on average have a higher TFP than non-VC-backed firms. Further, we find that low-reputation VCs screen firms with higher levels of initial TFP (averaged across 5 years prior to receiving financing) compared to high-reputation VCs. When we analyze the growth in firm TFP after receiving VC financing, we find that post-financing TFP growth is significantly greater for high-reputation VCs, suggesting that high-reputation VCs are better at improving productivity levels through

[47] We use a seemingly unrelated regression technique to compare the coefficients across the two equations estimated for high and low reputation VC backed firms. In unreported regressions, we also estimated our results in a single regression, where we interacted the VC reputation dummy with our $VCBefore_{it}$ and $VCAfter_{it}$ variables. Our results remain qualitatively unchanged. We choose to report these results as it is easier to interpret the coefficients and the differences between the coefficients in the two categories of VC reputation, in this set-up. Also, it provides for a more parsimonious display of the results.

monitoring compared to low-reputation VCs. We show that the above net effect of monitoring is both statistically and economically significant, on average being 10% higher for firms receiving funding from high-reputation VCs compared to firms receiving funding from low-reputation VCs. Our analysis presents an interesting and hitherto undocumented result, suggesting that most of the productivity gains of firms backed by low-reputation VCs can be attributed to the screening technology employed by such VCs, while on the other hand, most of the productivity gains of firms that are backed by high-reputation VCs come from the ability of such VCs to improve the post-financing TFP of firms they invest in, i.e., through their monitoring activities. This is not surprising since high-reputation VCs have greater experience and expertise in managing entrepreneurial firms and therefore are able to provide additional extra-financial services to these firms that ultimately result in better operating efficiency and performance. The higher net effect of 10% on firm TFP arising due to better monitoring by high-reputation VCs translates to an increase in profits of approximately 35% as mentioned previously. These results are also somewhat related with earlier empirical work by Gompers and Lerner (1999) who find that profit shares are higher for older and larger VCs. Similarly, these results are also related with those in Kaplan and Schoar (2005), who analyze both VC and buyout fund returns and show that there is a large degree of heterogeneity among fund returns. They show that returns tend to improve with the experience of the general partner. The above results establish that financing from reputable VCs (who are potentially also more experienced) lead to higher operating efficiency and TFP of their portfolio firms. Thus, when high-reputation VCs exit their investments it could potentially lead them to realize the higher returns that have been documented by the above papers.

In Panel B of Table 12, we analyze the round by round improvements in firm TFP for firms backed by high and low-reputation VCs. Consistent with the results above, we first show that the TFP of firms backed by low-reputation VCs is significantly greater than the TFP of firms backed by high-reputation VCs prior to receiving VC financing, suggesting that low-reputation VCs screen firms with higher initial levels of TFP. However, the results also show that after each round of receiving VC financing, the TFP of firms backed by high-reputation VCs is significantly greater than the TFP of firms backed by low-reputation VCs, again suggesting that high-reputation VCs are better able to increase the post-financing efficiency of firms due to their better monitoring abilities. The results on the round by round improvement in firm TFP for high and low-reputation VCs show that the TFP improvements after VC backing is much greater for firms backed by high reputation VCs than for those backed by low reputation VCs.

Overall, our results are consistent with higher reputation VCs providing greater monitoring services to the firms that they back, since these firms experience greater improvements in their productivity subsequent to VC financing.[48]

6.2 Differences in Channels of TFP Improvements between High and Low Reputation VC-backed Firms

In this section, we further disentangle the channels through which efficiency improvements are realized and investigate if there are differences in the underlying process of efficiency improvements between firms backed by high-reputation VCs and those backed by low-reputation VCs. Moreover, we also present evidence on how greater efficiency (TFP) improvements are realized by high-reputation VCs. We do so by estimating the joint covariance matrix for (3) estimated for high and low-reputation VC-backed firms as in Table 12. In Table 13, we investigate the dynamics of total sales and total production costs around the year of receiving the first round of VC financing for firms backed by high and low-reputation VCs, benchmarked against that of non-VC-backed firms.[49]

Panel A of Table 13 presents the results for total sales for high and low-reputation VC-backed firms benchmarked against non-VC-backed firms. The results show that prior to receiving financing, total sales for both high and low-reputation VC-backed firms is significantly greater than that of non-VC-backed firms. Moreover, at this time, total sales for firms backed by high-reputation VCs is greater than that of firms backed by low-reputation VCs, with the difference being on average around 2%. Subsequent to receiving VC financing, we also find that the growth in sales (from before to after receiving financing) is significantly greater for firms that are backed by high-reputation VCs compared to those backed by low-reputation VCs with the difference in sales growth being on average around 2.5%. Thus, the larger improvement in TFP achieved by high-reputation VC-backed firms, documented in Table 12, could partially be explained

[48] In unreported tests, we also run the switching regression and the counterfactual analyses from Tables 7 and 8, to control for the endogenous matching between entrepreneurial firms and high and low reputation VC backed firms. We find that TFP growth would have been smaller for high-reputation VC-backed firms had they received financing from low-reputation VCs instead. Similarly, TFP growth would have been greater for low-reputation VC-backed firms had they received financing from high-reputation VCs. In addition, we also conduct a propensity score matched analysis comparing propensity score matched sample adjusted TFP growth of high and low reputation VC-backed firms. We find significantly greater post-financing matched sample adjusted TFP growth for high reputation VC-backed firms relative to low reputation VC-backed firms.

[49] In unreported tests, we have investigated other components of input, i.e., materials, labor, and capital. We find a similar pattern of a lower change in materials cost and capital expendiure (from before to after) for high-reputation VC-backed firms compared to low reputation VC-backed firms. We also find that, in the long run (after 5 years) the increase in labor cost increases more for high reputation VC backed firms in the short run and lower for high-reputation VC-backed firms in the long run, compared to high reputaiton VC-backed firms. This is consistent with high-reputation VCs initially employing more skilled labor as suggested by Hellmann and Puri (2002).

by this better product market performance through increased sales growth of high-reputation VC-backed firms compared to low-reputation VC-backed firms.

Panel B presents the results for the total production costs fof high and low reputation VC-backed firms. We find that total production cost is consistently lower for high-reputation VC-backed firms compared to low-reputation VC-backed firms both before and after receiving VC financing, even though it is significantly above that of non-VC-backed firms. Moreover, the increase in production cost from before receiving financing to after receiving financing is also lower for firms that are backed by high-reputation VCs, suggesting that active monitoring by high-reputation VCs may lead to lower increases in cost for these firms, thus leading to more efficient production and higher productivity gains for high-reputation VC-backed firms compared to low-reputation VC-backed firms. This lower increase in total production cost for high-reputation VC-backed firms is on average around 1.5% in the first 4 years after receiving financing and around 7.5% in years 5 and after, both of which are statistically and economically significant.

The results presented in this section clearly show us how high-reputation VC-backed firms are able to achieve higher levels of productivity and efficiency improvements compared to firms backed by low-reputation VCs. It also shows us how better monitoring abilities of high-reputation VCs may be reflected through the production technology. We establish that the higher improvements in TFP and efficiency achieved by high-reputation VC-backed firms comes from both better product market performance by such firms, through higher sales realizations, as well as through various cost reductions associated with the production process. These results therefore attest to the better monitoring ability of high-reputation VCs, who are able to achieve better sales using lower input levels and thus are able to attain higher levels of productivity improvements for the firms they invest in.

7 Impact of Screening and Monitoring on the Probability of Exit

In this section, we analyze the effect of VCs on the exit probability of the firms and whether the increased productivity of VC-backed firms lead to a higher probability of a successful exit. We relate VC-backing and the pre- and post-VC financing operating efficiency or the TFP of a firm to its probability of exit either through an IPO or through a merger/acquisition (M&A) as opposed to a write-off. We first analyze the effect of VC-backing and TFP growth on the probability of a successful exit using a multinomial logit model. By analyzing the effect of pre-financing TFP and post-financing TFP growth, we are able

to distinguish between the TFP that may be attributable to the screening activities of the VC (prior to funding) and the TFP growth that is attributable to the monitoring activities of the VC (subsequent to funding). We estimate the follwing multinomial logit model.

$$Exit_Type = F\left(VC\ backing, TFP_Growth,\ Pre_VC_TFP,\ Firm_size, Controls\right) \tag{8}$$

where $Exit_Type$ is a dummy variable representing 3 categories, write-offs (the base category), M&As, and IPOs, where Pre_VC_TFP signifies the five year average TFP of VC-backed firms prior to receiving VC financing, i.e., the level of TFP that can be attributed to the screening activities of the VC, anf TFP_Growth is the current year TFP minus the average prior five year average TFP. In addition to firm size, we also control for firm age and Herfindahl index of the firm's industry. Our results for (8) are presented in Table 14.

We find that VC backing has a significant positive effect on the exit probability (for both IPO and M&A exits). Further, both The TFP growth in a year, and the prior average TFP have a positive relation with the exit probability though IPO, but not with the exit probability through acquisitions. Thus, TFP of firms attributed to both screening and monitoring activities of VCs positively affect the probability of exit through an IPO. In addition, we also find that firm size is positively related to the probability of a successful exit either through an IPO or an M&A, while younger firms are more likely to exit via an IPO. These results are consistent with those in the earlier literature (Chemmanur, He, and Nandy, 2010) showing that firms go public at the peak of their productivity cycle.

Overall, the results suggest that VC-backing has a positive impact on IPO and M&A exits, and further greater levels of pre-financing TFP and TFP growth that may be attributable to VC-backing also has a positive and significant association with the probability of IPO exits, but is not related to M&A exits.

8 Conclusion

In this paper, we have conducted the first large sample study of the role of venture capitalists in creating product market value for entrepreneurial firms using a unique database covering both private and public firms in the U.S. manufacturing sector obtained from the Longitudinal Research Database (LRD) of the U.S. Bureau of Census. We address several related questions regarding the efficiency gains

generated by VC investment in private firms. First, does VC backing improve the efficiency (total factor productivity, TFP) of private firms, and are certain kinds of VCs (high-reputation versus low-reputation) better at generating such efficiency gains than others? Second, how are such efficiency gains generated: Do VCs invest in more efficient firms to begin with (screening) or do they improve efficiency after investment (monitoring)? Third, how are these efficiency gains spread out over different rounds subsequent to VC investment? Fourth, what are the channels through which such efficiency gains are generated: increases in product market performance (sales) or reductions in various costs (labor, materials, production costs)? Finally, how do such efficiency gains affect the probability of a successful exit (IPO or acquisition)?

Our main findings are as follows. First, the overall efficiency of VC-backed firms is higher than that of non-VC-backed firms. Second, this efficiency advantage of VC-backed firms arise due to both screening and monitoring: the efficiency of VC-backed firms prior to receiving financing is higher than that of non-VC-backed firms and further, the growth in efficiency subsequent to receiving VC financing is greater for such firms relative to that for non-VC-backed firms. On average, VCs select firms that have higher TFP of around 6% compared to non-VC-backed private firms, and further VC firms are able to achieve an increase in their TFP of around 10% due to the monitoring services provided by VCs. Both these effects are economically significant, resulting in increases in profits of approximately 21% and 35% due to screening and monitoring, respectively. Third, the above increase in efficiency of VC-backed firms relative to non-VC-backed firms arises over the first two rounds subsequent to receiving financing, and remains higher till exit. Fourth, while the efficiency of firms prior to VC financing is lower for firms backed by high-reputation VCs, the increase in efficiency subsequent to financing is significantly greater for such firms, consistent with high-reputation VCs having greater monitoring ability compared to low-reputation VCs. Our results indicate that this difference in monitoring ability between higher and low-reputation VC-backed firms results in TFP improvements that are 4% greater for high-reputation VC-backed firms, which is economically very significant as it implies an increase in profits of approximately 18%. Fifth, the efficiency gains generated by VC backing arise primarily from improvement in product market performance (sales); however, for high-reputation VCs, these efficiency gains arise also from smaller increases in production costs. Finally, both the level of efficiency of VC-backed firms prior to receiving financing and the growth in efficiency subsequent to VC financing positively affect the probability of a successful exit, especially through an IPO.

This paper documents several new results in the literature. First, we present a comprehensive study

on productivity and efficiency gains in VC and non-VC-backed private firms in the U.S. manufacturing sector and show that VC-backed firms have higher levels of productivity compared to non-VC-backed firms. Second, we show that low-reputation VCs invest in firms with higher levels of TFP prior to financing, while high-reputation VCs achieve greater improvements in TFP in the firms they invest in, consistent with such VCs having greater monitoring ability. Third, we document the potential channels through which productivity increases from VC backing and show that high-reputation VC-backed firms realize greater TFP both from increases in sales as well as through lower increases in costs compared to low-reputation VC-backed firms. Finally, we show that VC-backed firms have a greater probability of exiting through an IPO or an M&A and that both pre-financing TFP and TFP growth subsequent to VC financing have a greater impact on the probability of an exit through an IPO, but not through an acquisition.

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Technical Appendix: Switching Regression Model

In the discussion that follows, we describe the switching regression model for the two outcome case reflecting the choice for a firm receiving VC financing versus not receiving VC financing. However, with minor adjustments, the analysis can easily be extended to account for more than two outcomes, such as a firm's choice between receiving VC financing from a high-reputation VC versus receiving financing from a low-reputation VC versus not receiving VC financing at all. In implementing this extension of the dichotomous choice model to that of a polychotomous choice model, we follow the approach outlined in Lee (1983), who provides the framework in a multinomial logit-OLS two-stage estimation method.

In the case of the dichotomous choice model, a switching regression model with endogenous switching consists of a binary outcome equation that reflects the selection or matching between the VC and the firm, and two regression equations on the variable of interest, in this case *TFP growth*. Formally, we have:

$$I_i^* = Z_i^{'}\gamma + \varepsilon_i, \tag{9}$$

$$y_{1i} = x_i^{'}\beta_1 + u_{1i}, \text{ and} \tag{10}$$

$$y_{2i} = x_i^{'}\beta_2 + u_{2i}. \tag{11}$$

Equation (9) is the latent VC-firm matching equation. To reflect binary outcomes, I^* is discretized as follows:

$$I_i = 1 \text{ iff } I_i^* > 0, \text{ and } I_i = 0 \text{ iff } I_i^* \leq 0. \tag{12}$$

In other words, I_i equals one if and only if a firm receives VC financing.[50] In this setup, the VC–firm matching is modeled in reduced form. The dependent variable I_i indicates the outcome of whether a firm receives VC financing, which results from decisions of both the firm and the VC and the screening technology adopted by the VC. Accordingly, in the empirical specification, the vector Z_i contains variables that might matter for either party as discussed in the text. In the dichotomous choice case, we estimate this first stage equation using a dynamic probit model where the dependent variable is a binary dummy, identifying whether a firm receives VC backing or not, while in the polychotomous choice case we estimate the first stage equation using a dynamic multinomial logit model.[51] In unreported tests, we find similar results to those in Table 7 for the polychotomous choice case with some differences: the coefficient on the number of plants is positive and significant for the low-reputation VC group only, while the coefficient on industry risk is negative and significant for the high-reputation VC group only. Further, we find that the bubble period is positively correlated with receiving financing from low-reputation VCs. As expected, the coefficient on fraction of instate LPs is positive and significant for the high-reputation group, suggesting that greater fraction of instate LPs lead to a higher VC reputation given the local availability of investors and thus VC reputation is correlated with greater fund raising capabilities of a VC firm.

Equation (10) analyzes the growth in TFP after receiving financing for VC-backed firms while controlling for selection effects, while equation (11) does the same for firms that did not receive VC financing. To estimate the model, a key observation is that since either equation (10) or (11) is realized depending on the outcome of I^* (but never both), the observed TFP growth is a conditional variable. Taking expectations of equation (10), we obtain:

[50] In the case of the polychotomous choice model, if I_i is the polychotomous variable with values 1 to M and if category s is chosen, then $I_i = s$ if and only if $Z_s\gamma_s + \varepsilon_s > 0$.

[51] The dependent variable is equal to zero always for all non-VC backed firms. For VC backed firms, it is zero in all years prior to receiving VC financing and it equals 1 in the year the firm receives VC financing and is set to missing in the following years. Thus, in the first stage, VC backed firms effectively drop out of the sample for all years subsequent to the year of receiving financing.

$$
\begin{aligned}
E[y_{1i}] &= E[y_i \mid I_i = 1] \\
&= E[y_i \mid I_i^* > 0] \\
&= E[X_i^{'}\beta_1 + u_{1i} \mid Z_i^{'}\gamma + \varepsilon_i > 0] \\
&= X_i^{'}\beta_1 + E[u_{1i} \mid \varepsilon_i > -Z_i^{'}\gamma] \qquad (13)
\end{aligned}
$$

Because u_1 and ε are correlated, the last conditional expectation term in (13) does not have a zero mean, and OLS on equation (10) will generate inconsistent estimates. If, however, equation (10) is augmented with the Inverse Mills ratio from the first stage probit estimation as a right-hand-side variable, we can use OLS to find consistent estimates. This procedure is discussed in detail in Heckman (1979) and Maddala (1983). Equation (9) is first estimated by a probit regression, yielding consistent estimates of γ. With this, the inverse Mills-ratio terms can be computed for equations (10) and (11). Both equations are then augmented with the inverse Mills ratios as additional regressors.[52] These terms adjust for the conditional mean of u, and allow the equations to be consistently estimated by OLS.[53]

One can compute the hypothetical TFP growth for VC-backed firms had they not received VC financing using equation (11) and the hypothetical TFP growth for non-VC-backed firms had they received VC financing using equation (10). Thus, to infer the monitoring effects of VCs on firm TFP growth, we compute the following difference:

[52] The standard errors in the second stage are bootstrapped to account for generated regressors.

[53] For the polychotomous choice model, the first stage is estimated using a multinomial logit model and the procedure is discussed in detail in Lee (1983). He shows that in this setting, the inverse Mills ratio is given by: $-\sigma\rho_1 \frac{\phi(J_{\epsilon 1}(0|\Gamma))}{F_{\epsilon 1}(0|\Gamma)}$, where ϕ is the standard normal density function, $J_{\epsilon 1}(.|\Gamma) = \Phi^{-1}(F_{\epsilon 1}(.|\Gamma))$, Φ is the standard normal cumulative, and $F_{\epsilon 1}(.|\Gamma)$ is the cumulative distribution function of ϵ_1. Since the inverse Mills ratio is negative in this case, we compute the inverse Mills ratio as the negative of the above function for ease of interpretation. Thus, in our case, the presence of private information should be reflected in the coefficient of the inverse Mills ratio being positive and significant in the second stage, which is what we find in unreported regressions.

$$\underbrace{y_{1i}}_{\text{actual}} - \underbrace{E[y_{2i} \mid I_i^* > 0]}_{\text{hypothetical}} \tag{14}$$

The first term in (14) is the actual TFP growth of a VC-backed firm, while the second is the hypothetical TFP growth that would be obtained by the same firm had it not received VC financing. If the difference is positive, then the impact on TFP growth due to the monitoring services provided by the VC is explicitly quantified, since the actual TFP growth achieved by VC-backed firms is higher. The same logic also holds for non-VC-backed firms as well as for high and low-reputation VC-backed firms.

Table 1: Industry and Year Distribution of VC-backed Firms Matched to LRD

This table reports the distribution of VC-backed manufacturing firms from the VentureXpert database matched to LRD across two-digit SIC code industries and year of first round of VC financing. Any investment made by VC funds for buyout or acquisition purposes or where the purpose of the first round of investment was unknown or missing in the Venture-Xpert database were removed from the sample prior to the matching. The sample period is from 1972 to 2000.

Panel A: Industry Distribution

2-Digit SIC Code	Industry Description	Freq.	Percent
20	Food and kindred products	61	3.24
22	Textile mill products	30	1.59
23	Apparel and other textile products	35	1.86
24	Lumber and wood products	25	1.33
25	Furniture and fixtures	18	0.96
26	Paper and allied products	32	1.7
27	Printing and publishing	96	5.1
28	Chemicals and allied products (Biotech)	95	5.05
29	Petroleum and coal products	10	0.53
30	Rubber and miscellaneous plastics products	68	3.62
31	Leather and leather products	25	1.33
32	Stone, clay, and glass products	67	3.56
33	Primary metal industries	227	12.07
34	Fabricated metal products	82	4.36
35	Industrial machinery and equipment (Computers)	320	17.01
36	Electronic and other electric equipment (Telecom)	355	18.87
37	Transportation equipment	45	2.39
38	Instruments and related products	247	13.13
39	Miscellaneous manufacturing industries	43	2.29

Panel B: Year Distribution

Year of First VC Financing	Freq.	Percent
1972	18	0.96
1973	29	1.54
1974	16	0.85
1975	24	1.28
1976	24	1.28
1977	30	1.59
1978	53	2.82
1979	46	2.45
1980	71	3.77
1981	102	5.42
1982	101	5.37
1983	119	6.33
1984	94	5
1985	78	4.15
1986	85	4.52
1987	69	3.67
1988	83	4.41
1989	86	4.57
1990	55	2.92
1991	24	1.28
1992	42	2.23
1993	34	1.81
1994	31	1.65
1995	76	4.04
1996	69	3.67
1997	93	4.94
1998	145	7.71
1999	94	5
2000	90	4.78

Table 2: Summary Statistics of VC and Non-VC-backed Firms

This table reports summary statistics for the sample of VC and similar birth cohort non-VC-backed firms, from the manufacturing sector (SIC 2000-3999) in the LRD between 1972 and 2000. Total Assets (in thousands of dollars) is constructed via the perpetual inventory method and is the sum of building assets *plus* machinery assets. Total Sales is the total value of shipments in thousands of dollars. Materials Cost is the expenses for the cost of materials and parts purchased, resales, contract work, and fuel and energy purchased, in thousands of dollars. Salaries and Wages is the sum of total salaries and wages of the firm in thousands of dollars. Firm Age at VC financing is the number of years since the firm first appeared in the LRD sample to the year of first round of VC financing. High Tech. Firm is the percentage of firms in the sample that are high tech. companies (i.e., belonging to 3 digit SIC codes 357, 366, 367, 372, 381, 382, 384). Herfindahl Index is a measure of concentration of the firm's 3 digit SIC industry. Industry risk is the standard-deviation of total value of shipments calculated over the prior five year period in the same 3 digit SIC industry as the sample firm. Firm Market share is the firm's market share in terms of sales in the same 3 digit SIC industry. To comply with the U.S. Census Bureau confidentiality requirements we report Quasi-Medians which are the average of the 43rd and the 57th percentile for each variable. All observations are at the firm-year level. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively. Statistical significance for differences of means and quasi-medians differences correspond to t-tests and rank-sum tests, respectively. Panel A reports statistics for VC versus non-VC-backed firms. Panel B reports statistics in the year of receiving VC financing for VC-backed firms that received VC financing in census years (1972, 1977, 1982, 1987, 1992, 1997) compared to those that received VC financing in non-census years. Variables are winsorized at the 1% and 99% levels.

Panel A: Venture and Non-Venture Backed Firms from LRD

		Venture Backed Firms	Non Venture Backed Firms	Difference
Total Assets	Mean	8109	1069.45	7039.55***
	Quasi-Median	1687.59	195.1	1492.49***
	Observations	1881	50114	
Total Sales	Mean	32730.22	5531.58	27198.64***
	Quasi-Median	10976.41	1926.3	9050.11***
	Observations	1881	50114	
Total Employment	Mean	250.64	53.08	197.57***
	Quasi-Median	106	26	80***
	Observations	1881	50114	
Materials Cost	Mean	15844.71	2816.96	13027.75***
	Quasi-Median	4688	755	3933***
	Observations	1881	50114	
Salaries and Wages	Mean	6306.24	1171.83	5134.41***
	Quasi-Median	3054	541.5	2512.5***
	Observations	1881	50114	
Firm Age at VC Financing	Mean	8.78		
	Quasi-Median	3		
	Observations	1881		
High Tech. Firm	Mean	0.36	0.06	0.30***
	Observations	1881	50114	
Industry Risk	Mean	3768.82	1166.06	2602.76***
	Quasi-Median	1925.14	720.16	1204.99***
	Observations	1881	50114	
Firm Market Share	Mean	0.01	0.00	0.01***
	Quasi-Median	0.00045	0.00015	0.0003***
	Observations	1881	50114	

Panel B: Venture Backed Firms Receiving the First Round of VC Financing in Census and Non-Census Years

		Census Year	Non-Census Year	Difference
Total Assets	Mean	8234.00	8080.12	153.88
	Quasi-Median	1969.06	1587.88	381.18
Total Sales	Mean	33701.59	32505.82	1195.77
	Quasi-Median	12219.04	10634.01	1585.04
Total Employment	Mean	259.58	248.58	11.01
	Quasi-Median	113.50	105.00	8.50
Material Costs	Mean	16415.86	15712.76	703.10
	Quasi-Median	5545.00	4505.50	1039.50
Salaries and Wages	Mean	6424.42	6278.94	145.48
	Quasi-Median	3277.50	2958.00	319.50
Firm Age at VC financing	Mean	7.798	9.005	-1.207
	Quasi-Median	2	2.50	-0.50*
High Tech. Firm	Mean	0.38	0.36	0.03
Industry Risk	Mean	3849.20	3750.31	98.90
	Quasi-Median	1870.52	1946.87	-76.35
Market Share	Mean	0.01	0.01	0.00
	Quasi-Median	0.00043	0.00046	-0.00003

Table 3: TFP Dynamics around Year of VC Financing

This table reports results for panel data regressions where the dependent variable is the TFP of a firm for a given year. The independent variables in Panel A are: *VCAfter,* which is a dummy variable that equals 1 for years after the firm gets the first round of VC financing and 0 otherwise; *VCBefore(-4,0)*, which is a dummy variable that equals 1 for years -4 to 0 prior to obtaining the first round of VC financing and 0 otherwise; *VCAfter(1,4)*, which is a dummy variable that equals 1 for years 1 to 4 after obtaining the first round of VC financing and 0 otherwise; *VCBefore(-t)* for all $0 \leq t \leq 4$, which equals 1 in year *t* before VC financing, and 0 otherwise; *VCAfter(t)* for all $0 \leq t \leq 4$, which equals 1 in year *t* after VC financing, and 0 otherwise; *VCAfter(≥ 5),* which equals 1 in or after year 5 of VC financing and 0 otherwise; *Firm Size*, which is the natural log of the firm's capital stock in a given year; *Herfindahl Index,* which is the concentration of the firm's 3 digit SIC industry; and firm and year fixed effects. Panel A reports the regression coefficient estimates and their statistical significances. Panel B reports TFP changes over various time periods and their statistical significances. Heteroskedasticity corrected robust standard errors, which are clustered on firms, are in brackets. All regressions are estimated with an intercept term. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A: Regression Results for TFP Changes Over Time

	(1)	(2)	(3)	(4)
VCAfter	0.121***			
	[0.030]			
VCBefore(-4,0)		0.068***	0.068***	
		[0.021]	[0.021]	
VCAfter(1,4)		0.120***		
		[0.032]		
VCBefore(-4)				0.042*
				[0.022]
VCBefore(-3)				0.088***
				[0.025]
VCBefore(-2)				0.086***
				[0.026]
VCBefore(-1)				0.053*
				[0.027]
VCBefore(0)				0.071**
				[0.030]
VCAfter(1)			0.108***	0.108***
			[0.034]	[0.035]
VCAfter(2)			0.106***	0.106***
			[0.035]	[0.035]
VCAfter(3)			0.13***	0.13***
			[0.035]	[0.035]
VCAfter(4)			0.136***	0.137***
			[0.039]	[0.039]
VCAfter(≥ 5)		0.188***	0.189***	0.189***
		[0.042]	[0.042]	[0.043]
Firm Size	-0.057***	-0.057***	-0.057***	-0.057***
	[0.003]	[0.003]	[0.003]	[0.003]
Herfindahl Index	-0.019	-0.018	-0.018	-0.018
	[0.020]	[0.020]	[0.020]	[0.020]
Firm Fixed Effects	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y
Observations	524806	524806	524806	524806
Adjusted R-Square	0.414	0.414	0.414	0.414

Panel B: TFP Change over Time				
	(1)	(2)	(3)	(4)
VCAfter(1,4) - VCBefore(4,0)		0.052**		
		[0.021]		
VCAfter(≥ 5) - VCBefore(4,0)		0.119***		
		[0.033]		
VCAfter(1) -VCBefore(4,0)			0.040*	
			[0.024]	
VCAfter(2) -VCBefore(4,0)			0.038	
			[0.026]	
VCAfter(3) -VCBefore(4,0)			0.062**	
			[0.026]	
VCAfter(4) -VCBefore(4,0)			0.069**	
			[0.029]	
VCAfter(≥5) -VCBefore(4,0)			0.121***	
			[0.033]	
VCAfter(1) - VCBefore(1)				0.056*
				[0.029]
VCAfter(2) - VCBefore(1)				0.054*
				[0.029]
VCAfter(3) - VCBefore(1)				0.077***
				[0.030]
VCAfter(4) - VCBefore(1)				0.084***
				[0.032]
VCAfter(≥ 5) - VCBefore(1)				0.136***
				[0.036]

Table 4: TFP Dynamics around Year of VC Financing for Early and Late Stage Firms.

This table reports results for panel data regressions where the dependent variable is the TFP of a firm for a given year. The regression results are reported for sub-samples of Early and Late stage firms, where an early stage firm is a firm that receives first round of VC financing at the early or startup/seed stage. The independent variables in Panel A are: *VCBefore(-4,0)*, which is a dummy variable that equals 1 for years -4 to 0 prior to obtaining the first round of VC financing and 0 otherwise; *VCAfter(1,4)*, which is a dummy variable that equals 1 for years 1 to 4 after obtaining the first round of VC financing and 0 otherwise; *VCAfter(≥ 5),* which equals 1 in or after year 5 of VC financing and 0 otherwise; *Firm Size*, which is the natural log of the firm's capital stock in a given year; *Herfindahl Index,* which is the concentration of the firm's 3 digit SIC industry; and firm and year fixed effects. Panel A reports the regression coefficient estimates and their statistical significances. Panel B reports TFP changes over various time periods and their statistical significances. Heteroskedasticity corrected robust standard errors, which are clustered on firms, are in brackets. All regressions are estimated with an intercept term. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A: Regression Results for TFP Changes Over Time		
	Early stage	Late Stage
VCBefore(-4,0)	0.067*	0.08***
	[0.039]	[0.023]
VCAfter(1,4)	0.201***	0.108***
	[0.069]	[0.028]
VCAfter(≥ 5)	0.313***	0.16***
	[0.095]	[0.03]
Firm Size	-0.064***	-0.065***
	[0.003]	[0.002]
Herfindahl Index	-0.013	-0.016
	[0.017]	[0.016]
Year Fixed Effects	Y	Y
Firm Fixed Effects	Y	Y
Observations	515581	520728
Adj. R-Squared	0.423	0.423

Panel B: TFP Changes Over Time		
VCAfter(1,4) - VCBefore(4,0)	0.133***	0.028
	[0.466]	[0.018]
VCAfter(≥ 5) - VCBefore(4,0)	0.246***	0.080***
	[0.073]	[0.029]

Table 5: Option and Stock Adjusted TFP Dynamics around Year of VC Financing

This table reports results for panel data regressions where the dependent variable is the TFP of a firm for a given year adjusted for option grants or stock and option grants. The first two columns report the results for TFP measures that are calculated assuming that option and stock grants in all years prior to 1992 are fixed at 1992 levels. The second two columns report the results for TFP measures that are calculated assuming that option and stock grants in years prior to 1992 decline going back in time at a constant imputed rate. The independent variables in Panel A are: *VCBefore(-4,0)*, which is a dummy variable that equals 1 for years -4 to 0 prior to obtaining the first round of VC financing and 0 otherwise; *VCAfter(1,4)*, which is a dummy variable that equals 1 for years 1 to 4 after obtaining the first round of VC financing and 0 otherwise; *VCAfter(≥ 5),* which equals 1 in or after year 5 of VC financing and 0 otherwise; *Firm Size*, which is the natural log of the firm's capital stock in a given year; *Herfindahl Index,* which is the concentration of the firm's 3 digit SIC industry; and firm and year fixed effects. Panel A reports the regression coefficient estimates and their statistical significances. Panel B reports TFP changes over various time periods and their statistical significances. Heteroskedasticity corrected robust standard errors, which are clustered on firms, are in brackets. All regressions are estimated with an intercept term. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A: Regression Results for TFP Changes Over Time				
	Option adjusted, Fixed level pre-1992	Stock and Option adjusted, Fixed level pre-1992	Option adjusted, Declining level pre-1992	Stock and Option adjusted, Declining level pre-1992
VCBefore(-4,0)	0.06***	0.06***	0.06***	0.06***
	[0.019]	[0.019]	[0.019]	[0.019]
VCAfter(1,4)	0.098***	0.095***	0.100***	0.098***
	[0.024]	[0.024]	[0.024]	[0.024]
VCAfter(≥ 5)	0.118***	0.116***	0.118***	0.115***
	[0.026]	[0.026]	[0.026]	[0.026]
Firm Size	-0.062***	-0.062***	-0.062***	-0.062***
	[0.003]	[0.003]	[0.003]	[0.003]
Herfindahl Index	-0.034	-0.034	-0.033	-0.033
	[0.023]	[0.023]	[0.023]	[0.023]
Year Fixed Effects	Y	Y	Y	Y
Firm Fixed Effects	Y	Y	Y	Y
Observations	524402	524402	524402	524402
Adj. R-Squared	0.381	0.381	0.381	0.381

Panel B: TFP Changes Over Time				
VCAfter(1,4) - VCBefore(4,0)	0.037*	0.035*	0.040**	0.038**
	[0.019]	[0.019]	[0.019]	[0.019]
VCAfter(≥ 5) - VCBefore(4,0)	0.058**	0.055**	0.058**	0.056**
	[0.023]	[0.023]	[0.023]	[0.023]

Table 6: TFP Dynamics around Rounds of VC Financing

This table reports results for panel data regressions where the dependent variable is the TFP of a firm for a given year. Panel A reports the regression results. The independent variables in the regression are *VCBefore*, which is a dummy variable that equals 1 for all years prior to the first round of VC financing and 0 otherwise; *VCAfter(R1)*, which is a dummy variable that equals 1 for years after the first round but before the second round of VC financing and 0 otherwise; *VCAfter(R2)*, which is a dummy variable that equals 1 for years after the second round but before the third round of VC financing and 0 otherwise; *VCAfter(R3)*, which is a dummy variable that equals 1 for years after the third round but before the fourth round of VC financing and 0 otherwise; *VCAfter(≥R4)*, which is a dummy variable that equals 1 for years after the fourth round of VC financing and 0 otherwise; *Firm Size*, which is the natural log of the firm's capital stock in a given year; *Herfindahl Index,* which is the one year lagged value of the measure of concentration of the firm's 3 digit SIC industry; and firm and year fixed effects. Panel A reports the regression coefficient estimates and their statistical significances. Panel B reports TFP changes over various rounds and their statistical significances. Heteroskedasticity corrected robust standard errors, which are clustered on firms, are in brackets. All regressions are estimated with an intercept term. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A: Regression Results for TFP Change Over Rounds	
VCBefore	0.057***
	[0.020]
VCAfter(R1)	0.102***
	[0.033]
VCAfter(R2)	0.192***
	[0.048]
VCAfter(R3)	0.189***
	[0.060]
VCAfter(≥R4)	0.155***
	[0.046]
Firm Size	-0.057***
	[0.003]
Herfindahl Index	-0.016
	[0.020]
Firm Fixed Effects	Y
Year Fixed Effects	Y
Observations	523750
Adj. R-Squared	0.414

Panel B: TFP Change Over Rounds	
VCAfter(R1) - VCBefore	0.045*
	[0.026]
VCAfter(R2) - VCBefore	0.135***
	[0.043]
VCAfter(R3) - VCBefore	0.131**
	[0.056]
VCAfter(≥R4) - VCBefore	0.098**
	[0.043]
VCAfter(R2) - VCAfter(R1)	0.090**
	[0.039]
VCAfter(R3) - VCAfter(R2)	-0.004
	[0.060]
VCAfter(≥R4) - VCAfter(R3)	-0.03
	[0.056]

Table 7: Switching Regressions with Endogenous Switching for VC and Non-VC-backed Firms

This table reports the results from a endogenous switching regression model where the dependent variable in the first stage is whether a firm gets VC financing in a given year (*VC Backing Dummy*). The time series for each firm that gets VC financing terminates in the year of obtaining the first round of VC financing. The independent variables in the regressions are*: Average 5 year prior TFP*, which is the average TFP over the last five years starting from the current year; *Increase in NSF Applied Research Grants*, which is the average change over the last five years in the real National Science Foundation applied research grants ($ million); *Increase in NSF Basic Research Grants*, which is the average change over the last five years in the real National Science Foundation basic research grants ($ million); *AAA Spread,* which is the spread of AAA bonds over 5 year treasury bonds in the current year; *Number of LPs*, which equals the total number of limited partners that exist over the previous five years; *Fraction of instate LPs*, which is the fraction of the number of LPs in the past five years that are located in the state of the company; *Firm Size*, which is the one year lagged value of natural log of the firm's capital; *Number of Plants*, which is the natural logarithm of the one year lagged value of the number of plants in the firm; *Herfindahl Index,* which is the one year lagged value of the measure of concentration of the firm's 3 digit SIC industry; *Firm Age*, which is the natural logarithm one year lagged value of the number of years since the firm first appeared in the LRD sample; *Firm Market Share,* which is the one year lagged value of the firm's market share in terms of sales in the same 3 digit SIC industry; *Industry risk*, which is the one year lagged value of the median standard deviation of the total value of shipments calculated over a prior five year period for all firms in the same 3 digit SIC industry as the sample firm; *High Tech. Firm,* which is a dummy variable that takes the value 0 if the one year lagged value of the firm's three-digit SIC code is 357, 366, 367, 372, 381, 382, or 384; *80s Dummy*, which takes the value 1 for years between 1980 and 1989, and 0 otherwise; *90s Dummy*, which takes the value 1 for years between 1990 and 1998, and 0 otherwise; and *Bubble Dummy*, which takes the value 1 for years between 1999 and 2000, and 0 otherwise. The dependent variable in the second stage regression is the *TFP Growth,* which is defined as the difference between the average TFP over the next five years and the average TFP over the last five years starting from the current year. The independent variables in these regressions are the *Inverse Mills Ratio* from the first stage and all the independent variables from the first stage except for *Increase in NSF Applied Research Grants, Increase in NSF Basic Research Grants, Number of LPs, Fraction of instate LPs,* and *AAA Spread.* In the first stage regressions, heteroskedasticity corrected robust standard errors, which are clustered on firms, are in brackets; while in the second stage regressions bootstrapped standard errors, which are clustered on firms, are in brackets. All regressions are estimated with an intercept term. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

VC-backed vs. Non-VC-backed Firms

First Stage		Second Stage		
Dependent Variable: VC Backing Dummy		*Dependent Variable: TFP Growth*		
			VC-backed Firms	Non-VC-backed Firms
Number of LPs	0.0004**	Inverse Mills Ratio	0.212**	0.035
	[0.000]		[0.086]	[0.386]
Fraction of instate LPs	0.575*	Average 5 Year Prior TFP	-0.779***	-0.921***
	[0.311]		[0.062]	[0.009]
Increase in NSF Applied Research Grants	0.445***	Firm Size	0.068***	-0.027***
	[0.127]		[0.024]	[0.003]
Increase in NSF Basic Research Grants	-0.442**	Number of Plants	0.000	0.002**
	[0.193]		[0.001]	[0.001]
AAA Spread	-0.115**	Herfindahl Index	-0.086	-0.031
	[0.048]		[0.086]	[0.023]
Average 5 Year Prior TFP	0.093**	Firm Age	-0.002	-0.006***
	[0.043]		[0.003]	[0.001]
Firm Size	0.212***	Firm Market Share	-0.066	0.214**
	[0.012]		[0.110]	[0.097]
Number of Plants	0.005***	Industry Risk	-0.001	0.0004
	[0.001]		[0.001]	[0.0003]
Herfindahl Index	0.332*	High Tech. Firm	0.081	-0.003
	[0.194]		[0.05]	[0.023]
Firm Age	-0.005**	S&P 500 Returns	-0.009	0.003
	[0.002]		[0.025]	[0.002]
Firm Market Share	-0.015	80s Dummy	0.132***	0.008
	[0.36]		[0.041]	[0.006]
Industry Risk	-0.01*	90s Dummy	0.068	0.004
	[0.005]		[0.045]	[0.008]
High Tech Firm	0.571***	Bubble Dummy	0.101*	0.015
	[0.044]		[0.056]	[0.011]
S&P 500 Returns	0.078			
	[0.133]			
80s Dummy	0.231***			
	[0.087]			
90s Dummy	-0.025			
	[0.157]			
Bubble Dummy	0.296*			
	[0.152]			
		Firm Fixed Effects	Y	Y
Observations	361334	Observations	5714	292815
Chi sq.	1234.9***	Adj. R-Square	0.665	0.69

Table 8: Actual versus Hypothetical TFP Growth for VC and Non-VC-backed Firms

This table reports the result of a "what-if" analysis based on the results of the switching regression model in Table 7. It reports the actual TFP growth around the first round of VC financing for VC-backed firms, the TFP Growth if VC-backed firms did not receive VC financing, and the difference between actual and hypothetical TFP growths *(TFP Growth Improvement)*. The table also reports the TFP growth for non-VC-backed firms if they had received VC financing, the actual TFP growth of non-VC-backed firms, and the difference between the actual and hypothetical TFP growths *(TFP Growth Improvement)*. TFP growth is defined as the difference between the average TFP over the next five years and the average TFP over the last five years starting from the current year. P-values for paired t-tests and sign-rank tests are reported in parentheses. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively, for t test of mean difference. $^{+++}$, $^{++}$, and $^{+}$ represent statistical significance at the 1, 5, and 10 percent levels, respectively, for the rank-sum test.

Actual and Hypothetical TFP Growth for VC vs. Non-VC-backed Firms			
	Actual TFP Growth for VC-backed firms	TFP Growth for VC-backed firms if they had not obtained VC financing	TFP Growth Improvement
Mean	0.001	-0.184	0.185***,$^{+++}$
	Actual TFP Growth for non-VC-backed firms	TFP Growth for non-VC-backed firms if they had obtained VC financing	TFP Growth Deterioration
Mean	-0.029	0.014	-0.043***,$^{+++}$

Table 9: Regression Discontinuity Analysis for VC and Non-VC-backed Firms

This table reports the result of a regression discontinuity analysis. The first stage reports the results from a probit model where the dependent variable is whether a firm gets VC financing in a given year (*VC Backing Dummy*). The time series for each firm that gets VC financing terminates in the year of obtaining the first round of VC financing. The independent variables in the regressions are*: Indicator (Norm. Emp. >1)*, which is a dummy variable which equals 1 if the one year lagged ratio of the company's total employment to the maximum SBA size threshold eligible to receive support from the US Small Business Administration (SBA) is greater than 1, i.e., the firm is ineligible to obtain support from the SBA, and 0 otherwise; *Norm. Employment*, which is the one year lagged ratio of the company's total employment to the maximum SBA size threshold to be eligible to receive support from the US SBA; *Average 5 year prior TFP*, which is the average TFP over the last five years starting from the current year; *Firm Size*, which is the one year lagged value of natural log of the firm's capital; *Number of Plants*, which is the natural logarithm of the one year lagged value of the number of plants in the firm; *Herfindahl Index,* which is the one year lagged value of the measure of concentration of the firm's 3 digit SIC industry; *Firm Age*, which is the natural logarithm one year lagged value of the number of years since the firm first appeared in the LRD sample; *Firm Market Share,* which is the one year lagged value of the firm's market share in terms of sales in the same 3 digit SIC industry; *Industry risk*, which is the one year lagged value of the median standard deviation of the total value of shipments calculated over a prior five year period for all firms in the same 3 digit SIC industry as the sample firm; *High Tech. Firm,* which is a dummy variable that takes the value 0 if the one year lagged value of the firm's three-digit SIC code is 357, 366, 367, 372, 381, 382, or 384; and year dummies. The dependent variable in the second stage regression is the *TFP Growth,* which is defined as the difference between the average TFP over the next five years and the average TFP over the last five years starting from the current year. The independent variables in these regressions are the *predicted VC backing probability* from the first stage and all the independent variables from the first stage except for *Indicator (Norm. Emp.>1)*. In the first stage regression, heteroskedasticity corrected robust standard errors, which are clustered on firms, are in brackets; while in the second stage regression bootstrapped standard errors, which are clustered on firms, are in brackets. All regressions are estimated with an intercept term. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

First Stage		Second Stage	
Dependent Variable: VC Backing Dummy		*Dependent Variable: TFP Growth*	
Indicator (Norm. Emp. >1)	0.357***	VC Backing Prob. (predicted)	1.325***
	[0.046]		[0.453]
Average 5 Year Prior TFP	0.092**	Average 5 Year Prior TFP	-0.906***
	[0.041]		[0.009]
Norm. Employment	-0.001	Norm. Employment	-0.001
	[0.001]		[0.001]
Firm Size	0.153***	Firm Size	-0.023***
	[0.014]		[0.003]
Number of Plants	0.006***	Number of Plants	0.000
	[0.001]		[0.001]
Herfindahl Index	0.307	Herfindahl Index	-0.055**
	[0.19]		[0.022]
Firm Age	-0.007***	Firm Age	-0.005***
	[0.002]		[0.001]
Firm Market Share	0.267	Firm Market Share	0.086
	[0.341]		[0.081]
Industry Risk	-5.616	Industry Risk	0.868*
	[4.543]		[0.500]
High Tech Firm	0.595***	High Tech. Firm	-0.023
	[0.042]		[0.02]
		Firm Fixed Effects	Y
Year Fixed Effects	Y	Year Fixed Effects	Y
Observations	404332	Observations	312885
Wald Chi2	1365.53***	Adj R-sq.	0.685

Table 10: Matched Sample Comparison of TFP Growth after VC Financing

This table reports means and quasi-medians for *TFP Growth,* which is defined as the difference between the average TFP over the next five years and the average TFP over the last five years starting from the current year; and the *Average 5 year prior TFP*, which is the average TFP over the last five years starting from the current year. Quasi-medians are the average of the 43rd and the 57th percentile for each variable. We report quasi-medians rather than medians to comply with the U.S. Census Bureau confidentiality requirements. The matched sample is created using a propensity score based matching methodology. Matched firms are selected such that it is in the same three-digit SIC industry in the year of the VC financing of the sample firm and has comparable capital stock and average 5 year prior TFP as the sample firm. P-values are reported in parentheses. P-values for means and medians correspond to t-tests and sign-tests, respectively, for the null hypothesis that the mean and median are zero. P-values for differences in means and medians correspond to paired t-tests and sign-rank tests. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

		Sample	Matched	Diff.
TFP Growth	Mean	0.001***	-0.047	0.048*
	p-value	(0.007)	(0.959)	(0.051)
	Quasi-median	0.001***	-0.040	0.041**
	p-value	(0.004)	(0.650)	(0.041)
	Observations	558	558	
Average 5 year prior TFP	Mean	0.020	0.001	0.019
	p-value	(0.949)	(0.341)	(0.460)
	Quasi-median	0.040	0.010**	0.030
	p-value	(0.773)	(0.012)	(0.150)
	Observations	588	588	

Table 11: Dynamics of Inputs in TFP around the First Round of VC Financing

This table reports results for panel data regressions where the dependent variables are log total sales, log production cost, log capital expenditure, log materials cost, log salaries and wages, and log total employment of a firm for a given year. The independent variables are: *After,* which is a dummy variable that equals 1 for years after the firm gets the first round of VC financing and 0 otherwise; *VCBefore(-4,0)*, which is a dummy variable that equals 1 for years -4 to 0 prior to obtaining the first round of VC financing and 0 otherwise; *VCAfter(1,4)* , which is a dummy variable that equals 1 for years 1 to 4 after obtaining the first round of VC financing and 0 otherwise *VCAfter(≥ 5),* which equals 1 in and after year 5 of VC financing and 0 otherwise; *Firm Size*, which is the natural log of the firm's capital stock in a given year; and Firm and Year Fixed Effects. Panel A reports the regression coefficient estimates and their statistical significances. Panel B reports change in the dependent variable over various time periods and their statistical significances. Heteroskedasticity corrected robust standard errors, which are clustered on firms, are in brackets. All regression specifications are estimated with an intercept. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively

Panel A: OLS Regression

	Log Total Sales	Log Production Cost	Log Capital Exp.	Log Materials Cost	Log Salaries & Wages	Log Total Employment
VCBefore(-4,0)	0.147***	0.113***	0.152***	0.104***	0.062**	0.031
	[0.032]	[0.036]	[0.051]	[0.037]	[0.028]	[0.029]
VCAfter(1,4)	0.220***	0.180***	0.118**	0.182***	0.112***	0.063*
	[0.043]	[0.044]	[0.059]	[0.043]	[0.034]	[0.034]
VCAfter(≥ 5)	0.352***	0.293***	0.093	0.224***	0.103***	0.025
	[0.051]	[0.049]	[0.060]	[0.049]	[0.039]	[0.042]
Firm Size	0.593***	0.618***	1.040***	0.614***	0.581***	0.522***
	[0.005]	[0.006]	[0.008]	[0.006]	[0.005]	[0.005]
Year Fixed Effects	Y	Y	Y	Y	Y	Y
Firm Fixed Effects	Y	Y	Y	Y	Y	Y
Observations	546006	545941	552311	541722	546565	545239
Adj. R-Square	0.932	0.916	0.67	0.912	0.932	0.929

Panel B: Change in Dependent Variable Over Time

	Log Total Sales	Log Production Costs	Log Capital Exp.	Log Materials Cost	Log Salaries & Wages	Log Total Employment
VCAfter(1,4) - VCBefore(4,0)	0.072***	0.066**	-0.035	0.078***	0.050**	0.032
	[0.027]	[0.029]	[0.053]	[0.030]	[0.022]	[0.023]
VCAfter(≥ 5) - VCBefore(4,0)	0.205**	0.180***	0.059	0.120***	-0.041	0.006
	[0.037]	[0.036]	[0.057]	[0.038]	[0.031]	[0.033]

Table 12: TFP Changes around Year of VC Financing for High and Low Reputation VC Backed Firms. This table reports results for panel data regressions where the dependent variable is the TFP of a firm for a given year. The regression results are reported separately for high and low reputation VC backed firms. The independent variables in Panel A are: *VCAfter,* which is a dummy variable that equals 1 for years after the firm gets the first round of VC financing and 0 otherwise; *VCBefore(-4,0)*, which is a dummy variable that equals 1 for years -4 to 0 prior to obtaining the first round of VC financing and 0 otherwise; *VCAfter(1,4)*, which is a dummy variable that equals 1 for years 1 to 4 after obtaining the first round of VC financing and 0 otherwise; *VCBefore(-t)* for all $0 \leq t \leq 4$, which equals 1 in year *t* before VC financing, and 0 otherwise; *VCAfter(t)* for all $0 \leq t \leq 4$, which equals 1 in year *t* after VC financing, and 0 otherwise; *VCAfter(≥ 5),* which equals 1 in or after year 5 of VC financing and 0 otherwise; *Firm Size*, which is the natural log of the firm's capital stock in a given year; *Herfindahl Index,* which is the concentration of the firm's 3 digit SIC industry; and firm and year fixed effects. The independent variables in panel B (not reported in panel A) are *VCBefore*, which is a dummy variable that equals 1 for all years prior to the first round of VC financing and 0 otherwise; *VCAfter(R1)*, which is a dummy variable that equals 1 for years after the first round but before the second round of VC financing and 0 otherwise; *VCAfter(R2)*, which is a dummy variable that equals 1 for years after the second round but before the third round of VC financing and 0 otherwise; *VCAfter(R3)*, which is a dummy variable that equals 1 for years after the third round but before the fourth round of VC financing and 0 otherwise; *VCAfter(≥R4)*, which is a dummy variable that equals 1 for years after the fourth round of VC financing and 0 otherwise. Heteroskedasticity corrected robust standard errors, which are clustered on firms, are in brackets. All regressions are estimated with an intercept term. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A: TFP Regressions for High and Low Reputation Backed VCs

	High-reputation VC	Low-reputation VC	TFP Diff: (High - Low)	TFP Change Over Time Relative to VCBefore(-4,0): Diff. (High -Low)
VCBefore(-4,0)	0.07***	0.081***	-0.011***	
	[0.017]	[0.016]	[0.001]	
VCAfter(1,4)	0.174***	0.089***	0.085***	0.096***
	[0.018]	[0.018]	[0.001]	[0.000]
VCAfter(≥ 5)	0.262***	0.139***	0.122***	0.133***
	[0.017]	[0.017]	[0.001]	[0.000]
Firm Size	-0.064***	-0.064***		
	[0.001]	[0.001]		
Herfindahl Index	-0.014	-0.015		
	[0.011]	[0.012]		
Year Fixed Effects	Y	Y		
Firm Fixed Effects	Y	Y		
Observations	517718	518147		
Adj. R-Square	0.413	0.413		

Panel B: TFP Regressions Over Rounds for High and Low Reputation Backed VCs

	High-reputation VC	Low-reputation VC	TFP Diff.	TFP Change Over Rounds Relative to VCBefore: Diff. (High - Low)
VCBefore	0.055***	0.078***	-0.023***	
	[0.018]	[0.017]	[0.001]	
VCAfter(R1)	0.120***	0.093***	0.027***	0.050***
	[0.018]	[0.093]	[0.001]	[0.000]
VCAfter(R2)	0.280***	0.127***	0.153***	0.176***
	[0.026]	[0.029]	[0.001]	[0.001]
VCAfter(R3)	0.282***	0.155***	0.128***	0.151***
	[0.031]	[0.036]	[0.001]	[0.001]
VCAfter(≥R4)	0.265***	0.073*	0.192***	0.214***
	[0.036]	[0.042]	[0.001]	[0.001]
Firm Size	-0.065***	-0.064***		
	[0.001]	[0.001]		
Herfindahl Index	-0.012	-0.014		
	[0.012]	[0.012]		
Firm Fixed Effects	Y	Y		
Year Fixed Effects	Y	Y		
Observations	517130	517707		
Adj. R-Squared	0.413	0.412		

Table 13: Dynamics of Inputs in TFP around the First Round of VC Financing for High and Low Reputation VC-backed Firms

This table reports results for panel data regressions where the dependent variables are log total sales and log production cost for a given year. The regression results are reported separately for high and low reputation VC backed firms. The independent variables are: *VCBefore(-4,0)*, which is a dummy variable that equals 1 for years -4 to 0 prior to obtaining the first round of VC financing and 0 otherwise; *VCAfter(1,4)*, which is a dummy variable that equals 1 for years 1 to 4 after obtaining the first round of VC financing and 0 otherwise; *VCAfter(≥5),* which equals 1 in and after year 5 of VC financing and 0 otherwise; *Firm Size*, which is the natural log of the firm's capital stock in a given year; and Firm and Year Fixed Effects. Heteroskedasticity corrected robust standard errors, which are clustered on firms, are in brackets. All regressions are estimated with an intercept term. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A: Log Total Sales

	High-reputation VC	Low-reputation VC	Diff. (High - Low)	Diff. in growth relative to VCBefore(-4,0): (High -Low)
VCBefore(-4,0)	0.161***	0.141***	0.019***	
	[0.091]	[0.018]	[0.001]	
VCAfter(1,4)	0.250***	0.205***	0.045***	0.025***
	[0.020]	[0.020]	[0.001]	[0.001]
VCAfter(≥5)	0.379***	0.362***	0.017***	-0.002
	[0.019]	[0.019]	[0.001]	[0.002]
Firm Size	0.568***	0.567***		
	[0.001]	[0.001]		
Year Fixed Effects	Y	Y		
Firm Fixed Effects	Y	Y		
Observations	538216	538627		
Adj. R-Square	0.932	0.932		

Panel B: Log Production Cost

	High-reputation VC	Low-reputation VC	Diff. (High - Low)	Diff. in growth relative to VCBefore(-4,0): (High -Low)
VCBefore(-4,0)	0.109***	0.112***	-0.003**	
	[0.024]	[0.022]	[0.001]	
VCAfter(1,4)	0.171***	0.189***	-0.018***	-0.015***
	[0.025]	[0.024]	[0.001]	[0.001]
VCAfter(≥ 5)	0.267***	0.345***	-0.078***	-0.075***
	[0.023]	[0.024]	[0.001]	[0.001]
Firm Size	0.586***	0.586***		
	[0.005]	[0.001]		
Year Fixed Effects	Y	Y		
Firm Fixed Effects	Y	Y		
Observations	538150	538562		
Adj. R-Square	0.917	0.917		

Table 14: Venture Capital Backing and IPO and Acquisition Frequency (Multinomial Logit)

This table reports the results of multinomial logit estimation with Type of Exit (i.e., No Exit, IPO, or M&A) as the dependent variable. No Exit is the base case outcome. The dependent variables are, *VC backing*, which is a dummy variable that is 1 for firms that obtain VC financing; *TFP Growth*, which is the TFP Growth calculated as current year TFP minus the prior five year average TFP; *Average Prior TFP*, which is the five year average TFP prior to the current year; *Firm Size*, which is the natural log of the firm's capital stock in the current year; *Herfindahl Index,* which is the measure of concentration of the firm's 3 digit SIC industry; *Firm Age*, which is the natural logarithm of the number of years since the firm first appeared in the LRD sample; and year dummies and 3 digit SIC industry dummies. Heteroskedasticity corrected robust standard errors, which are clustered on firms, are in brackets. The regression is estimated with an intercept term. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

	IPO	M&A
VC backing	1.119***	1.655***
	[0.184]	[0.153]
TFP Growth	0.360***	0.024
	[0.120]	[0.094]
Average prior TFP	0.292**	0.037
	[0.130]	[0.097]
Firm Size	0.434***	0.305***
	[0.028]	[0.027]
Firm Age	-0.031***	0.003
	[0.006]	[0.005]
Herfindahl Index	0.231	0.525
	[0.510]	[0.540]
Industry Fixed Effects	Y	
Year Fixed Effects	Y	
Observations	405798	
Chi-Sq.	216807.7	
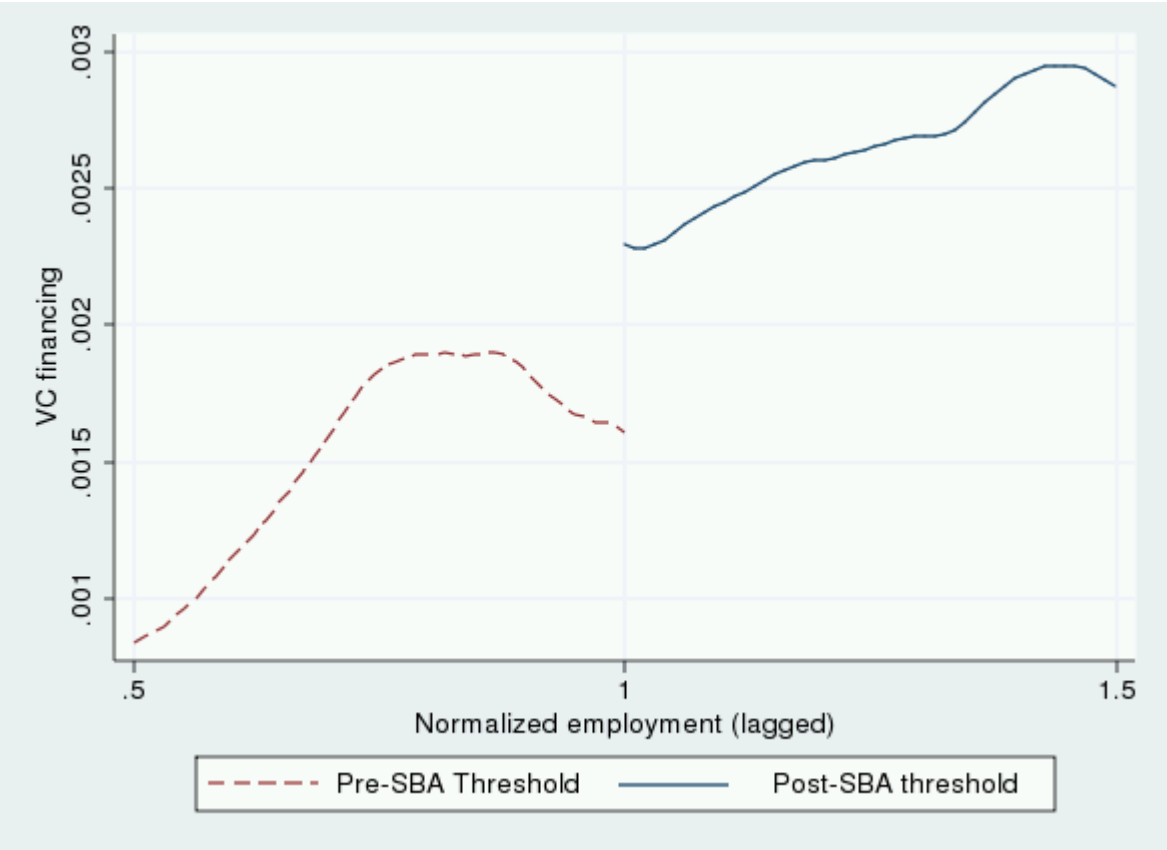
Figure 1: Discontinuity of the Treatment (VC Financing) when Normalized Employment=1