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

Thomas Chemmanur*

Karthik Krishnan**

and

Debarshi Nandy***

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* Professor, Finance Department, Fulton Hall 440, Carroll School of Management, Boston College, Chestnut Hill, MA 02467, Tel: (617) 552-3980, Fax: (617) 552-0431, email: chemmanu@bc.edu

** Ph.D. Candidate, Finance Department, Fulton Hall 341, Carroll School of Management, Boston College, Chestnut Hill, MA 02467, Tel: (617) 552-2033, Fax: (617) 552-0431, email: krishnkb@bc.edu

*** Assistant Professor, Finance Area, Room N226 SSB, Schulich School of Business, York University, 4700 Keele Street, Toronto, Ontario, Canada M3J 1P3, Tel: (416) 736-2100 Ext. 77906, Fax: (416) 736-5687, email: dnandy@schulich.yorku.ca

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Abstract

Using a unique sample from the Longitudinal Research Database (LRD) of the U.S. Census Bureau, we study several related questions regarding the efficiency gains generated by venture capital (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 (higher reputation versus lower reputation) better at generating such efficiency gains than others? Second, how are such efficiency gains generated: Do venture capitalists 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 time 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, total 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 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. Third, the above increase in efficiency of VC backed firms relative to non-VC backed firms is monotonically increasing over the four years subsequent to the year of initial VC financing, and continues till exit. Fourth, while the efficiency of firms prior to VC financing is similar across higher and lower reputation VC backed firms, the increase in efficiency subsequent to financing is significantly higher for the former firms, consistent with higher reputation VCs having greater monitoring ability. Fifth, the efficiency gains generated by VC backing arise primarily from improvement in product market performance (sales); however for high reputation VCs, the additional efficiency gains arise from both an additional improvement in product market performance as well as from reductions in various input 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 (IPO or acquisition).

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1 Introduction

The role of venture capital 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 venture capital literature have argued that, in addition to providing financing, venture capitalists provide other services to private firms which can considerably enhance the probability of success of these firms (see, e.g., Repullo and Suarez (1999) or Chemmanur and Chen (2003)). Practitioners also argue that in addition to providing funding for private firms, venture capitalists 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 higher reputation venture capitalists are better at providing the above services than lower reputation venture capitalists: see, e.g., Sahlman (1997) who states "From whom you raise capital is often more important than the terms."[1]

The above raises several interesting questions regarding the role played by venture capitalists in creating "*extra-financial*" value for private firms that they invest in. First, do venture-backed firms have better performance and higher operating efficiency than non-venture backed firms? Second, if indeed this is the case, precisely how do venture capitalists create value for private firms: are they able to identify and invest in higher quality entrepreneurial firms (*screening*), or does the value creation arise primarily from the various extra-financial services they provide to the firm (discussed earlier) subsequent to their investing in the firm (*monitoring*)? Third, are venture capitalists with better reputation more capable of creating value by improving the efficiency of firms they invest in? In particular, are higher reputation venture capitalists better at screening or monitoring (or both) than lower reputation venture capitalists? Finally, if the value-addition due to venture capital backing is at least partly due to monitoring, how are these value improvements spread over time: do they occur immediately after the venture capitalists invest in the firm, or do they occur in later years? While the answers to the above questions are empirical

[1] See also 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."

in nature, evidence on these issues is scarce, with some notable exceptions: see, e.g., Hellman and Puri (2000, 2002) who, however, focus only on the professionalization of start-up firms with the help of venture capitalists (Hellman and Puri (2002)) and the reduction in the time taken to bring a product to market due to venture capital affiliation (Hellman and Puri (2000)). Our first objective in this paper is to use a unique data covering both private and public firms in the U.S. manufacturing sector, obtained from the Longitudinal Research Database (LRD) maintained by the *Center of Economic Studies* of the U.S. Bureau of Census, to answer the above questions by conducting the first large sample study in the literature of the role of venture capital backing in improving the operating efficiency and performance of firms backed by them.

The second objective of this paper is to identify the precise channels through which venture capitalists improve the efficiency of private firms. Do these efficiency improvements arise from better aggregate product market performance (sales) of venture backed firms relative to non-venture backed firms? Or, do they arise from differences in various input costs of venture backed firms relative to non-venture backed firms? For example, do such efficiency improvements 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? In answering the above questions, we are able to disentangle differences between venture and non-venture backed firms on each of the above dimensions existing at the time of venture capital investment (screening) from those arising subsequent to investment by venture capitalists (monitoring). We also study whether efficiency improvements arising through the above channels are greater for firms backed by higher reputation venture capitalists compared to those backed by lower reputation venture capitalists.

Our third and final objective in this paper is to study how the efficiency advantages of venture backed firms 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. Further, we disentangle the effect of pre-existing advantages in efficiency possessed by venture backed firms prior to investment (i.e., screening) from efficiency advantages generated by venture capital backing (i.e., monitoring) on the probability of a successful exit. Finally, we will study how the above effects are different for private firms backed by higher reputation venture capitalists compared to those backed by lower reputation venture capitalists.

The results of our empirical analysis can be summarized as follows. We start by investigating whether venture backed firms are characterized by greater overall efficiency compared to non-venture backed firms. Similar to other papers that have used the LRD database to study various corporate events (see, e.g., Maksimovic and Phillips (2001), Schoar (2002), Chemmanur and Nandy (2003), and Chemmanur, He, and Nandy (2005)), we use Total Factor Productivity (TFP) as our measure of overall 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. In other words, an increase in TFP is an increase in the overall productivity 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. Therefore TFP is a particularly appropriate measure to analyze the increase in firm efficiency due to venture capital backing, since it captures productivity changes after accounting for increases in the scale of production. We find that the overall efficiency of venture backed firms (as measured by TFP) is higher than that of non-venture backed firms. In particular, we find that the TFP of venture backed firms prior to receiving venture financing is higher than that of non-venture backed firms and further, the growth in TFP subsequent to receiving venture financing is greater for venture backed firms relative to non-venture backed firms. We thus find evidence of both a screening and a monitoring role for venture capitalists in improving firm efficiency.

In our analysis of the dynamics of productivity growth, we document that the above improvement in TFP of venture backed firms relative to non-venture backed firms is monotonically increasing over the four years subsequent to the year of the first round of venture financing, and continues till exit. Finally, in our analysis of the effect of backing by high reputation versus low reputation venture capitalists, we document that while the TFP of firms prior to venture capital financing is similar across the two types of venture capitalists, the growth in TFP subsequent to financing is significantly higher for firms backed by higher reputation venture capitalists compared to those backed by lower reputation venture capitalists. This finding is consistent with higher reputation venture capitalists having greater monitoring ability compared to lower reputation venture capitalists.[2]

[2] In unreported results, we also analyze the round by round changes in TFP for venture backed firms. Overall, our results are consistent with those discussed above and show that TFP at every round is significantly greater than TFP prior to receiving financing. Moreover, consistent with earlier results, at every round and even prior to receiving VC financing, TFP of VC backed firms are significantly greater than the TFP of non-VC backed firms. Further, for VC-backed firms, the TFP in round 2 (i.e., between round 2 and 3) is significantly greater compared to 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. However, TFP increases after round 2 are not significantly greater than the TFP at round 2. When considering firms backed by high reputation VC's only, we obtain similar

In order to further disentangle the screening and monitoring effects of venture backing on firm efficiency, we employ two alternative methodologies. The first methodology we employ is "switching regressions with endogenous switching", which answers the following question: for a firm which received venture financing, what would its TFP growth have been, had it not received such financing? Clearly, the difference between the actual TFP growth of venture backed firms and the benchmark level estimated from the above "what if" analysis yields the TFP growth attributable to the monitoring effect of venture capital backing. Consistent with our earlier results, our switching regression results indicate a significantly positive effect of venture capital monitoring on TFP growth. Specifically, we find that VC-firm matching results in an equilibrium outcome; TFP growth declines for both VC and non-VC backed firms had the firms been in the other category, i.e., had VC backed firms not received VC financing and had non-VC backed firms received VC financing. The second methodology we employ is a matched sample analysis using the propensity score matching algorithm. Using this methodology, we match our sample of venture backed firms to non-venture 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 venture backed firms subsequent to receiving financing is significantly greater than that of matching firms, thus confirming the monitoring effect of venture backing on TFP growth. Our matched sample analysis further indicates that the above monitoring effect of venture backing is greater for higher reputation venture capitalists compared to lower reputation venture capitalists, again consistent with our earlier results.

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

patterns of TFP changes by rounds, with higher levels of significance. The results are however different for the low reputation sample. For these firms, even though the before and after coefficients are significant themselves (showing that VC backed firms have higher TFP than non-VC-backed firms), the difference in TFP between round 1 and before financing, and round 2 and before, are not significant. These results thus suggest, that low reputation VC's are unable to affect TFP growth through monitoring, consistent with our earlier results.

financing. However, the growth in total salaries and wages subsequent to receiving financing is greater for venture backed firms relative to non-venture backed firms, though the growth in the level of employment remains comparable across the two kinds of firms. Overall, the above results indicate that the primary channel through which venture backing improves efficiency is by improving product market performances (sales).

Our split-sample analysis of the channels through which high reputation and low reputation venture capitalists improve efficiency in firms backed by them indicate the following. First, the level of sales prior to receiving financing is lower for higher reputation venture capitalists compared to lower reputation venture capitalists; however, the growth in sales subsequent to financing is greater for higher reputation venture backed firms compared to lower reputation venture backed firms. Second, total production costs prior to venture financing is lower for higher reputation venture backed firms compared to lower reputation venture backed firms and the growth in total production costs subsequent to financing is also lower for higher reputation venture backed firms compared to low reputation venture backed firms. Similarly, while total labor costs prior to receiving venture financing are higher for higher reputation venture backed firms compared to lower reputation venture backed firms; the growth in total labor costs subsequent to financing is lower for higher reputation venture backed firms. These results are consistent with the notion that the primary channel through which both high and low venture capitalists improve efficiency is though improvements in product market performance (sales), however the additional improvements in efficiency generated by high reputation VCs arise through both improvements in product market performance (sales) and also through reductions in input costs.

Finally, the results of our analysis of the impact of the efficiency of venture backed firms on the probability of a successful exit can be summarized as follows. First, both the level of TFP of venture backed firms prior to receiving financing and the growth in TFP subsequent to financing positively affects the probability of a successful exit (either through an IPO or an acquisition). Second, our split sample analysis of high reputation versus low reputation venture backed firms indicate that, for high reputation venture backed firms, the probability of an exit through an IPO or an acquisition is increasing in both the level of TFP prior to financing and the TFP growth subsequent to financing. In contrast, for low reputation venture backed firms, it is the probability of an acquisition that is increasing in the above two variables. The above results are consistent with the notion that the efficiency improvements due to venture backing are long-lived and indeed result in successful outcomes. They also support the notion that firms with higher levels of efficiency are more likely to exit through an IPO rather than an acquisition.[3]

Our's is the first paper in the literature that compares the efficiency of venture backed and non-venture backed private firms, and analyzes the efficiency improvements arising from venture backing. Prior studies in the literature have focused only on the monitoring role of venture capital (see, e.g., Gompers (1995) and Lerner (1995)), and study only samples of venture backed firms. These papers therefore do not compare venture and non-venture backed firms, and rely on changes over time and differences within venture backed firms. Further, neither of the above two papers focus on the overall efficiency of venture backed private firms: Lerner (1995) examines venture capitalists' representation on the board of private firms and analyzes whether this representation is greater when the need for oversight is greater; Gompers (1995) studies the structure and outcome distribution (IPOs, acquisitions, bankruptcy, etc.) of a sample of venture capital investments and documents that venture capitalists concentrate their investments in early stage companies and high tech industries where informational asymmetries are significant and monitoring is valuable.[4] Hellman and Puri (2000) provide evidence that venture capital financing is related to the product market strategies and outcomes of start-ups. In particular, they show that venture capital is associated with a significant reduction in the time to bring a product to market, especially for innovators. Hellman and Puri (2002) study the role of venture capital in professionalizing the management of start-up firms, using measures such as human resource policies, the adoption of stock option plans, the hiring of a marketing VP. In a recent paper, Puri and Zarutskie (2007) study the life cycle dynamics of venture backed and non-venture backed firms. They show that venture capitalists disproportionately invest in firms that have no commercial sales but which exhibit high levels of investment, and that venture backed firms are larger than non-venture backed firms at every stage along their life cycle. Unlike our paper, they do not compare the efficiency of venture backed and non-venture backed firms; neither do they analyze the efficiency improvements arising due to venture backing.[5]

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

[4] Two other related papers are Kaplan and Stromberg (2000a and 2000b). The first paper studies the structure of venture capital contracts in the context of the existing theoretical literature. The second paper looks at investment memoranda to gauge venture capitalists' expectations at the time of funding, and finds that venture capitalists expect to help companies with managerial recruitment.

[5] Using a sample of venture backed firms, Sorensen (2007) show 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. Ueda and Hirukawa (2003) study the relationship between venture capital investments and innovation. Specifically, they analyze the following question: does venture capital investment stimulate innovation or is there a reverse causality? Our paper is also somewhat related with earlier empirical work by 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.

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

2 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.[6] 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).[7] 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. 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.[8] 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.

Two major difficulties in conducting research on VC financing and its effects on firms' performance are first, on 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,

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

[7] 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.

[8] 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.

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).[9] There are three major advantages of using the LRD relative to the LBD for this study. First, assets, sales, operating costs, profit measures, 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 firm performance, i.e., total factor productivity (TFP) can only be constructed for the LRD panel. Second, the nature of the LRD data 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. Third, the LRD panel starts from 1972 as opposed to the LBD which starts in 1975, thus providing us a longer panel of nearly three decades for our analysis.

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 VC's invest as well as the VC firms themselves. It provides information on the names and locations of venture capitalists who invest in each round of the firm, the number of such VC's, 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 27,399 firms whose first round of VC financing lies between 1946 and 2005. As the LRD covers firms located in the U.S. only, we first remove from our sample all firms that are not located within the U.S. Since we are interested in analyzing the impact of VC financing to entrepreneurial firms, we then 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, which leaves us with a sample of 15,253 firms. We then restrict our sample to firms that received their first round of VC financing between 1972 and 2000, which leaves us with 12,481 firms. We begin by trying to 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.[10] We employ standard matching procedures using the

[9] 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.

[10] 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).

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%.[11] We then merge this data to the LRD, which contains firms in the manufacturing sector (SIC codes 2,000 to 3,999), and 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. Panel A of Table 1 presents the industry distribution at the 2 digit SIC level of the 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 very much representative of what anecdotal evidence suggests, with some concentration in computers, biotech, electronics, and other high-tech industries such as precision instruments. Similarly, consistent with the practitioner literature and anecdotal evidence, one can also observe that VC investment in new firms peaked during the early 80's and also during the internet bubble period of the late 90's. Thus 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.[12],[13]

2.1 Measurement of Total Factor Productivity (TFP)

The primary measure of firm performance 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 (2005). The total factor productivity of the firm for each year is then

[11] A detailed description of such matching procedures employing name and address matching can be found in Puri and Zarutskie (2007). This match rate is comparable to that acheived by earlier studies, such as Chemmanur and Nandy (2004), Chemmanur, He, and Nandy (2005), and Puri and Zarutskie (2007).

[12] 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.

[13] 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 (2005)) and numerical identifiers for plants and firms provided in the LRD, which we discuss further below.

calculated as a weighted sum of plant Total Factor Productivity (TFP). 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.[14] Individual plants are indexed i; industries j; for each year t, in the sample:

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

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 is proportional to the actual quantity of output. Thus, the dispersion of TFP for firms in our sample almost entirely reflects dispersions in efficiency.

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 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.[15] Deflators for

[14] As a robustness check, we re-estimate the production function using two and three digit SIC industry classifications. We also estimate TFP with value added production function specifications and separate white and blue collar labor inputs. In all cases we find qualitatively equivalent results.

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

capital stock are available from the Bureau of Economic Analysis.[16] Plant level TFP is then computed as the residuals of regression (1), estimated 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. Thus, it is 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. Thus, TFP can be understood as the relative productivity rank of a plant within its industry in any given year. Since these regressions include a constant term, TFP only contains the idiosyncratic part of plant productivity.[17] 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.[18] The firm level TFP is then winsorized at the 1st and 99th percentile.

2.2 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

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

[17] 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) and Maksimovic and Phillips (2001). 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 productivity.

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

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 number of years since the firm first appeared in the LRD.[19] *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 expenses 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. In order to proxy for *Industry Risk*, we calculate the median standard deviation of firm sales over a prior five year period for all firms in the same 3 digit SIC industry as the sample 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 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. 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. We define VC reputation by the reputation of the VC syndicate that provides the first round of VC financing. *High Reputation* corresponds to the average market share of the VC syndicate, based on the amount raised by the VCs over a five year period prior to the date of VC financing, being above the sample median, while *Low Reputation* is if the average

[19] 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. Given the sampling scheme and scope of LRD, this measure is highly correlated with the actual age of the firm. Particularly, the relative age across firms, which is more relevant for our analysis, is captured very well by this measure.

market share is below the sample median level. 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 addition to the firm specific and industry wide controls mentioned above, we also use several variables as instruments in our regression analysis. As shown by Gompers and Lerner (1999) *Capital Gains Tax Rate*, affects the ability of VCs to secure commitments from investors and thereby proxies the propensity of VCs to invest in private firms. Decreases in the capital gains tax rates are associated with higher venture capital commitments, and therefore greater investments by VCs. Alternately, decreases in tax rates may also drive increases in the demand for VC investments as workers have greater incentives to become entrepreneurs. Additionally, 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.

3 Do Venture Capitalists Improve Firm Efficiency?

3.1 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. On average, firms that received VC financing are bigger than non-VC backed firms; while the median non-VC backed private firm has only 1 plant, the median VC backed firm has 2.5 plants in our sample in the LRD.

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.[20] All reported statistics are firm-year observations. We find that VC financed firms in our sample are on average larger than non-VC financed firms, in terms of asset value, sales, and total employment. Based on asset value, VC backed firms are on average 50 times larger than non-VC backed firms. In addition, the market share of VC backed firms is about 17 times greater than that of non-VC backed firms, suggesting that typically

[20] 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 43^{rd} and the 57^{th} percentile of each variable and closely approximates the true median value of the variables.

VC backed firms are market leaders in their industries. Total cost of materials and total salaries and wages for VC backed firms is also larger (on average about 40 times) than that of non-VC backed firms, consistent with the argument made by Puri and Zarutskie (2007) 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.

In our sample, we find that the average firm age of VC financed firms is greater that non-VC financed firms, implying that on average VC backed firms tend to remain (survive) in our sample for a longer period of time than non VC backed firms. This result provides some indirect evidence to the fact that VCs back firms that either have a higher probability of success *ex ante*, or survive longer than non VC backed firms due to the value additions provided by the VCs themselves - we analyze this in greater detail and provide direct evidence on this later on in this paper. It should also be noted that within the manufacturing sector, on average the age at which firms receive their first round of VC financing is approximately when they are 10 years old.[21] Finally, 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; we also analyze this in greater detail later on.

3.2 Univariate Comparison of TFP *Before* and *After* VC Financing

In this section we provide some basic evidence regarding the change in TFP of VC backed firms *before* and *after* receiving venture financing and also regarding the differences in TFPs of firms backed by high and low reputation VCs. In Panel A of Table 3, we first show the differences in TFP between VC backed and non-VC backed firms. Even prior to receiving VC financing, we find that VC backed firms are far more efficient, having on average 75% higher TFP compared to non-VC backed firms. Further, this difference in TFP between VC and non-VC backed firms increases even more to above 100%, subsequent to the VC financing. Second, we observe that the TFP for VC backed firms from prior to receiving financing to after receiving financing on average doubles in our sample. These simple univariate results suggest that VC backed firms are different than non-VC backed firms even before receiving financing from the

[21] The corresponding quasi-median level is approximately 8 years. This suggests, that unlike the service industry, where anecdotal evidence suggests that VCs tend to back firms that are much younger, in the manufacturing sector, it is not so.

VC; on average they have higher operating efficiency, suggesting that VCs are able to screen and select higher quality firms in which they invest. Further, the results also show that subsequent to funding, the operational efficiency of VC backed firms increase even further suggesting that VC financing indeed creates value for them.[22]

Panel B presents the results for differences in firm TFP between firms backed by high and low reputation VCs. Prior to receiving financing, the magnitude of TFP for firms backed by higher reputation VCs is larger than that for firms backed by lower reputation VCs, with the median being significantly different between the two categories. After receiving VC financing we find significant differences in both the mean and median TFP of firms backed by high and low reputation VCs. Specifically, the TFP of firms backed by higher reputation VCs is nearly triple that of firms backed by lower reputation VCs. These results therefore suggest, that the value addition to firms is much greater for those backed by higher reputation VCs than for firms backed by lower reputation VCs. In other words, higher reputation VCs contribute more towards the increase in firm efficiency through their monitoring abilities than lower reputation VCs. These results should, however, be interpreted with caution, since here, we do not benchmark the changes in firm TFP against a control sample of non-VC backed firms, do not account for other firm specific factors that may influence TFP changes, and also we do not properly attempt to control for the endogeneity of post VC financing increases in TFP due to the screening ability of the VCs; we do all this in our multivariate analysis that follows.

3.3 The Impact of Venture Capital Financing on Firm TFP

3.3.1 Impact of Screening and Monitoring of VCs on the Dynamics of TFP around the first round of VC Financing

In our subsequent analysis we use total factor productivity (TFP) as a comprehensive index of firm efficiency.[23] First, we consider the effect of VC financing on subsequent TFPs of firms that receive VC

[22] It is important to remember that our sample represents an unbalanced panel of firm-year observations. Since in our sample, VC financing is dispersed through time, generally the number of years we observe a firm prior to VC financing will not be equal to the number of years we observe that firm subsequent to financing and prior to its exit. Thus, the above unbalancedness of our panel does not arise due to any obvious survivorship bias.

[23] It is important to note that since TFP is computed from the residuals of four-digit SIC-year regressions, which includes as independent variables factors that determine the scale of production in the firm, 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 completely independent of the scale of production. This is specially important in light of our summary statistics and that of earlier studies that highlight the importance of scale in VC financing.

financing vis-à-vis those that do not. Second, we document the dynamic pattern of TFP changes both *before* and *after* the first round of VC funding, 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 *efficient contracting* and *monitoring* activities of VCs subsequent to funding.[24] We employ a regression framework to analyze these effects, where we first include firm and year fixed effects which allows us to precisely control for any cross-sectional differences between firms and across time, which helps us to somewhat isolate the impact of screening on TFP. Second, as VC financing of firms are distributed over time, by defining an *VC After* dummy we easily allow for the staggering of the events, and 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 (2005), where he 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:

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

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

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

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.[25] In (3), we introduce $VCBefore_{-4,0}$, which is a dummy variable that

[24] It should be noted that it is not possible for us to differentiate between the effect of contracting and monitoring 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 simply 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.

[25] 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

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 5^{th} 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 round of financing. Finally, we also control for lagged values of TFP in these specifications. 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, $VCAfter^s_{it}$ 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.[26] The dynamic pattern of the effect of VC financing on TFP is captured by the coefficients δ^s_1 and δ^s_2. In all specifications i indexes firms, t indexes years, and β_i are firm fixed effects. The specifications also include year dummies. 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.

Panel A of Table 4 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 $VCBefore$.[27] As can be seen from Table 4, VC's actively engage in both screening and monitoring, broadly consistent with the evidence presented in Sorensen (2007).[28] Furthermore, this activity

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.

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

[27] 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 technique 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 endogeneity issue.

[28] Unlike us, Sorensen (2007) does not have data on non VC backed private firms. It should also be noted that 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 has been noted in the literature in several prior studies (e.g., see Gompers (1995), Gompers and Lerner (1999), Sahlman (1990) etc.), 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 on each other. Screening, on the other hand refers to the VC's ability to select better performing

of the VCs greatly improve the performance and efficiency of the firms that they are involved with. *Reg 2* to *Reg 5* in Table 4 panel A shows that, on average, firms financed by VC's have 6% higher TFP over the 5 years prior to receiving funding, compared to firms that do not obtain VC financing, indicating that VC's actively screen firms prior to funding and select the ones with higher levels of efficiency, based on their private information.[29] Furthermore, subsequent to funding, TFP of VC backed firms improve even further, on average to 10% over the next 4 years, over and above non-VC backed firms, suggesting that VC's actively monitor their investments and improve the performance and efficiency of firms they fund through this mechanism. This result is robust to adding lagged vales of TFP as regressors to (3) showing that this improvement in TFP subsequent to VC funding is independent of any trend in TFPs. Finally, *Reg 6* 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 outperformed 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 6% relative to non-VC firms, similar to the earlier results. After receiving funding, we do observe an increasing trend of TFP for VC backed firms for 5 years after the first round of financing, of approximately 10%, suggesting that the involvement of VC's and their monitoring of these firms led 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) receiving funding 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 *Reg1* to *Reg 6* are significant at the 1% level.

Panel B of Table 4 presents the net effect on firm TFP that can be attributed to the monitoring abilities of VCs. Based on *Reg 2* to *Reg 5*, we find that the average increase in TFP from before receiving VC financing to 4 years after receiving VC financing is around 5% for VC backed firms. This increase is around 10% for the VC backed firms when we compute the difference in TFP after year 5. In *Reg 6*, we compute the net effect of monitoring year by year for VC backed firms. Consistent with the evidence presented so far, we observe that there is a monotonically increasing effect of VC monitoring on TFP (benchmarked to the year prior to receiving VC financing). 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 5^{th} year

firms in the presence of information asymmetry and based on their private information.

[29] 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 captures the private information possessed by the VC about that firm in that particular year.

subsequent to the first round of financing.[30] Overall, the results from Table 4 suggest that VCs actively engage in both screening and monitoring. On average, we find that due to their screening ability, VC's 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%. Moreover, this net impact of monitoring monotonically increases with the number of years since receiving the first round of VC financing. 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, translates to an increase in profits of approximately 21% and 35% respectively.[31],[32]

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

[30] 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 since receiving VC funding 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 that a VC engages in, is positively correlated to the amount of investment made in the firm. Thus, as VC's invest additional funds, their level of monitoring could also increase, leading us to observe the increasing net effect of monitoring on TFP for the years that are further away from the initial year of investment.

[31] 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*.

[32] As explained before, under the assumption that TFP and profits are positively correlated, our result implies that VC backed firms should also be more profitable. However, Puri and Zarutskie (2007) find that VC backed firms are no more profitable than non-VC backed firms before exit. One simple explanation for this is that while we study firms within the manufacturing sector, they include firms across all industries in their study. Thus, the differences in our results could potentially be driven by the fact that unlike the manufacturing sector, firms in the services sector, such as "internet firms", rarely have any tangible assets or sales when they source financing. Anecdotal evidence suggests that such firms receive VC financing purely based on the idea or the concept that they come up with and hence, on average, these firms are also much younger. Further, as anecdotal evidence also suggests, for manufacturing firms it is crucial to at least have a product prototype and partial infrastructure in place to manufacture the product, in order to receive VC financing. Moreover, these firms are also more mature and older compared to firms in the services sector.

3.3.2 Impact of Screening and Monitoring: Differences in TFP Dynamics between High and Low Reputation VCs

In this section we pursue our earlier goal of quantifying the impact of screening and monitoring on firm TFP and further analyze how these impacts might differ between high and low reputation VCs. As discussed earlier in the introduction, there is reason to believe that given the choice, entrepreneurs would prefer to source financing from higher reputation VCs. Hsu (2004) points out that a financing offer from a higher reputation VC is approximately three times more likely to be accepted by an entrepreneur and also that higher 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 higher reputation VCs provided superior monitoring and management, subsequently leading to better firm performance. In this section our aim is to empirically show this. We do so, by jointly estimating (3) in a seemingly unrelated regression framework, for both high and low reputation VCs.[33] We present 2 different specifications, with the second specification controlling for lagged values of TFP. The results are presented in Table 5, with column (1) and (2) corresponding to high and low reputation VCs respectively, column (3) presenting the difference in TFPs before and after the financing between high and low reputation VCs, and column (4) presenting the difference in the net effect of monitoring (i.e., $TFP_{After} - TFP_{Before}$) between high and low reputation VCs. The following discussion is based on the second specification, where we control for lagged TFP.

Consistent with our earlier results we find, that both high and low reputation VCs actively engage in screening and are able to select firms that on average have a higher TFP of around 7% over and above that of non-VC firms. We find that this screening effect is similar across VC reputation - both high and low reputation VCs screen firms that have similar higher levels of productivity vis-a-vis non-VC firms prior to receiving financing.[34] Moreover, we find that the impact of monitoring on firm TFP is significantly greater for high reputation VCs. While for high reputation VCs, TFP improvements during the first four years, as

[33] We use the seemingly unrelated estimation technique in order to directly compare the coefficients between the high and low reputation VC samples. The exact same coefficients are also obtained when estimating the two panel regressions separately. 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. Moreover, it also provides for a more parsimonious display of the results.

[34] Even though our results indicate that there is a statistical difference at the 10% level in the TFP of firms screened by high and low reputation VCs, the magnitude is extremely small being in the order of 0.1%. Thus, one can easily make the argument that economically, there is no difference in the screening ability of high and low reputation VCs.

well as years five and beyond after financing are substantial, it is not so for the low reputation VCs - for this group there is no improvement in TFP during the first four years after receiving financing. 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 low reputation VCs over and above that of non-VC backed firms. Our analysis presents an interesting and hitherto undocumented result, suggesting that screening technologies employed by VCs are similar across VC reputation. The additional benefit that entrepreneurs receive in securing funding from a high reputation VC comes completely from the monitoring activities that such VCs provide to the firm and this increase in firm efficiency is realized in the years immediately following the investment. This is not surprising since higher 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 net effect of 10% on firm TFP due to this better monitoring technology of high reputation VCs translates to an increase in profits of approximately 35% as mentioned previously.

It should however be noted that low reputation VCs also provide some monitoring services that are overall beneficial to firms, even though they are only realized five years or after receiving the first round of financing - on average their monitoring efforts result in performance improvements of 5% compared to non-VC firms that do not receive VC financing. Thus, while both the monitoring services provided by low and high reputation VCs lead to efficiency improvements for their portfolio firms compared to non-VC backed firms, the efficiency improvements captured by reputable VC backed firms is on average double that of non reputable VC backed firms. Again all variables of interest are statistically significant at the 1% level as are the differences in the coefficients between high and low reputation VCs. These results are also tangentially related with earlier empirical work by Gompers and Lerner (2000) who find that profit shares are higher for older and larger VCs. Similarly, 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 also show that returns tend to improve with the experience of the general partner. Our results establish that financing from reputable VCs lead to better performance and higher operating efficiency of their portfolio firms. Thus, when VCs exit such investments it could potentially lead them to realize the higher returns that have been documented by these papers.

3.4 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. In this section, we adopt a more general structure and employ switching regressions with endogenous switching to isolate the impact of screening on TFP. Anecdotal evidence suggests that VCs screen firms and thus the VC-firm matching is nonrandom. As such, this treatment 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. As shown earlier in Table 2, firm and industry characteristics for VC backed and non-VC backed firms are remarkably different. VC backed firms seem to be larger, more riskier, and have a larger market share than non-VC backed firms, all of which highlight the endogenous nature of the VC-firm matching process. To correctly measure the monitoring effect, what we are interested in is the following "what-if" type of question: For a firm financed by a VC, what would the alternative future performance be *had it not received* VC financing. Similarly, for a firm that did not receive VC financing, what would the alternative future performance be *had it received* VC financing. The answer to this question holds the impact on TFP due to screening constant, and separates out the effect of monitoring on firm TFP due to VC financing.

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:

$$I_i^* = Z_i^{'}\gamma + \varepsilon_i, \tag{5}$$

$$y_{1i} = x_i^{'}\beta_1 + u_{1i}, \text{ and} \tag{6}$$

$$y_{2i} = x_i^{'}\beta_2 + u_{2i}. \tag{7}$$

Equation (5) is the latent VC-firm matching equation. To reflect binary outcomes, I^* is discretized as follows:

$$I_i = 1 \text{ iff } I_i^* > 0, \text{ and } I_i = 0 \text{ iff } I_i^* \leq 0. \tag{8}$$

In other words, I_i equals one if and only if a firm receives VC financing. 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. Firm-level characteristics that could affect the matching include the average prior five year 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 include the industry Herfindahl index and the riskiness of the industry in which the firm operates; market wide characteristics include the *S&P500* return, and time dummies capturing the 80s, the 90s, and the internet-bubble period. In addition, we also include two instruments, the capital gains tax rate and the AAA spread, that affect the availability of funds to the VCs which may in turn affect the screening technology employed by them, as argued by Gompers and Lerner (1999). These instruments provide us with a certain degree of exogenous variation both in terms of supply of, and demand for VC funds, which affects the selection equation (i.e., the matching outcome) but does not directly affect the impact on firm performance due to VC monitoring. 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.[35] The results presented in Table 6 shows that prior TFP growth, firm size, number of plants operated by the firm, industry risk, high tech firms, and the technology-bubble dummy are all positive and highly significant determinants of receiving VC financing. As expected, both the instruments and firm age are negative and significant determinants of VC financing, suggesting that availability of funds to VCs is an important criterion for VC financing, consistent with Gompers and Lerner (1999) and that VC's typically fund private firms that are in the early stages of formation consistent with the arguments of Hellmann and Puri (2000, 2002).

Equation (6) analyzes the impact of this matching on TFP growth for the VC backed firms, while equation (7) does the same for firms that did not receive VC financing. Using these two equations, one can compute the hypothetical TFP growth for the VC backed firms had they not received VC financing

[35] 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 these firms then drop out of the sample for all years subsequent to receiving financing.

using equation (7) and also the hypothetical TFP growth for non-VC backed firms had they received VC financing using equation (6). Of course, for each firm, we only observe either y_{1i} or y_{2i}, depending on the outcome of I_i, so that the following observation rules hold:

$$y_i = y_{1i} \text{ iff } I_i = 1, \text{ and } y_i = y_{2i} \text{ iff } I_i = 0. \tag{9}$$

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 and in Song (2007) in her study on the differences between commercial banks and investment banks as bond underwriters. Further, Li and Prabhala (2007) provides a nice survey of this methodology. This is a generalization of the Heckman style two-stage model where instead of the two second stage equations, for the VC backed and non-VC backed firms that we have here, there is one second-stage equation, which in effect restricts the beta coefficients in equations (6) and (7) to be the same across receiving and not receiving VC funding. Relaxing the equality of the beta coefficients makes this model more general.

To estimate the model, a key observation is that since either equation (6) or (7) is realized depending on the outcome of I^* (but never both), the observed TFP growth is a conditional variable. Taking expectations of equation (6), we obtain:

$$\begin{aligned} E[y_{1i}] &= E[y_i \mid I_i = 1] \\ &= E[y_i \mid I_i^* > 0] \\ &= E[X_i'\beta_1 + u_{1i} \mid Z_i'\gamma + \varepsilon_i > 0] \\ &= X_i'\beta_1 + E[u_{1i} \mid \varepsilon_i > -Z_i'\gamma] \end{aligned} \tag{10}$$

Because u_1 and ε are correlated, the last conditional expectation term in (10) does not have a zero mean, and OLS on equation (6) will generate inconsistent estimates. If, however, equation (6) is augmented with the Inverse Mills ratio from the first stage probit estimation, added to the regression as a right-hand-side variable, we can then use OLS to find consistent estimates. This procedure is discussed in detail in Heckman (1979) and Maddala (1983). Equation (5) is first estimated by a probit regression, yielding consistent estimates of γ. With this, the inverse Mills-ratio terms can be computed for equations (6) and (7). Both equations are then augmented with the inverse Mills ratios as additional regressors. These terms adjust for the conditional mean of u, and allow the equations to be consistently estimated by OLS. The second stage results also presented in Table 6, shows that the inverse Mill's ratio is positive and significant for both equations, for the VC backed firms as well as the non-VC backed firms, suggesting that private information that VCs and firms have about each other and the VC's decision to invest in some firms or the firm's decision to receive financing from VCs (due to the double sided matching), indeed affect the future TFP growth of firms. The result indicates that the private information that leads to this matching positively affects the future performance of both VC backed firms as well as non-VC backed firms, suggesting that the matching results in an optimal or equilibrium outcome, where neither group can do better by deviating. Comparing the coefficients across the two groups we find that while in general larger firms, younger firms, firms operating a greater number of plants, and high tech firms achieve higher TFP growth in the future, the marginal impact of some of these variables on TFP growth is more pronounced for VC backed firms. Further, for non-VC backed firms, the results show that TFP growth is negatively related to firm market share, suggesting that productivity improvements are not realized for non-VC backed firms that are market leaders.

To infer the monitoring effects of VCs on firm TFP growth, we compute the following difference:

$$\underbrace{y_{1i}}_{\text{actual}} - \underbrace{E[y_{2i} \mid I_i^* > 0]}_{\text{hypothetical}} \tag{11}$$

The first term in (11) 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, as the actual TFP growth achieved by the VC backed firms is higher.

Table 7 presents some very interesting results. The top half of Table 7 shows that due to the monitoring services provided by the VC, on average VC backed firms achieved better efficiency and performance of approximately 9% than what the *same firms* would have achieved had they not received VC financing. The magnitude of this improvement is consistent with our earlier results presented in Table 4 and is also both statistically and economically significant, since it corresponds to around an 31.5% increase in profits during the first 5 years after receiving financing. Consistent with the idea of optimal matching, our results also show that if the non-VC backed firms had received VC financing, then they would have performed worse, with a decrease in TFP growth of about 1.2%, which is also statistically and economically significant. Thus, our results from tables 6 and 7 empirically show that VCs and firms optimally match with each other and this matching represents an equilibrium outcome where both groups of firms are better off, which is consistent with anecdotal evidence that suggests that not every firm would benefit from VC financing; while for some firms the benefits of such financing outweighs the costs associated with it, for others the costs outweigh the benefits and thus VC financing for these firms is suboptimal. The VC-firm matching seems to account for these potential costs and benefits of receiving VC financing and yields VC-firm matches that turn out to be ex-post efficient and in equilibrium. In summary, our analysis in this section explicitly accounted for the endogenous matching and screening of VC backed firms using a Heckman style two-stage model and we find qualitatively similar results as in the previous section. Moreover, we empirically show, for the first time in the literature, that VC-firm matching results in an equilibrium outcome that is ex-post efficient.

3.5 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. In this methodology, 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 5 year prior TFP in the year 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. Panel A of Table 8 presents the results for our two portfolios of firms. By definition as per our construction, we see that 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 VC backed firms realized significantly positive TFP growth (both at the mean and the quasi-median), the matched sample of non-VC backed firms did 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 7% higher and the quasi-median being approximately 5% higher than the matched 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 being similar to that documented in the earlier sections.

In Panel B of Table 8, we further investigate the difference in TFP growth between high and low reputation VCs, generated due to the monitoring activities of VCs. In this panel, we present the differences for the matched firm adjusted TFPs for both the high and low reputation VC backed firms. Again, as per our construction, we see that there is no difference between the average five year prior TFP for both high and low reputation VC backed firms to their matched non-VC backed firms. When we compare the TFP growth over the next five years, we observe that while the TFP growth is significantly higher for high reputation VC backed firms, it is not so for the low reputation VC backed firms. The difference in TFP growth between the high and low reputation backed firms is approximately 9% with the differences between the distributions of the two samples being statistically different. This result is consistent with our earlier findings in Table 5, suggesting that the impact of monitoring on TFP growth is significantly greater for firms backed by higher reputation VCs, supporting our notion that high reputation VCs generate higher improvements in firm efficiency through their monitoring activities.

4 The Channels through which Venture Capitalists Improve Firm Efficiency

4.1 The Average Effect Across All Firms

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 9. For each dependent variable we present two specifications: one with and one without the lagged dependent variables. We control for firm size and include both firm specific and year fixed effects and cluster the standard errors at the firm level. Panel A of Table 9 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 costs for firms from before receiving VC financing to after receiving financing. This increase in total production costs mainly arises from increases in materials costs. Compared to non-VC backed firms, total labor costs are similar in VC backed firms prior to receiving financing, but increase subsequent to receiving VC financing. While materials costs increase monotonically after receiving VC funding, the increase in labor costs is only evident during the first four years after receiving VC financing; for five years and after, we do not find a significant difference in the growth of salaries and wages from before receiving financing as compared to non-VC backed firms. We also find no changes in the level of total employment from before receiving VC financing to after receiving financing. Finally, we document that capital expenditures are not significantly different between VC backed and non-VC backed firms both prior to receiving financing and after receiving financing.[36] Put together, the results presented in Table 9 suggest that the increase in efficiency of VC backed firms, that we documented earlier, on average do not come about through decreases in the cost structure of firms, but rather 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 Hellman and Puri (2002).

4.2 Differences 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 higher reputation VCs. We do so by jointly estimating (3) in a seemingly unrelated regression framework, for both high and low reputation

[36] This result is sentitive to controlling for past capital expenditures of the firms. As can be seen from our results in Table 9, in the first specification, when we do not control for lags in capital expenditure in our regressions, we reach the potentially biased conclusion that VC backed firms invest more than non-VC backed firms.

VCs as in Table 5. In each panel of Table 10, we investigate the dynamics of one of the variables that may affect the TFP of the firm, such as output (total sales) 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, for firms backed by both high and low reputation VCs. The results are presented in Table 10.

Panel A of Table 10 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. However, at this time, total sales for firms backed by higher reputation VCs is lower than that of firms backed by lower reputation VCs, with the difference being on average around 1%. Subsequent to receiving VC financing however, we 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 1.4%. Thus, the larger improvement in TFP achieved by high reputation VC backed firms, documented in Table 5, could partially be explained by this better product market performance through increased sales growth of high reputation VC backed firms compared to low reputation VC backed firms. Moreover, the initial lower sales and the subsequent higher growth in sales of high reputation VC backed firms also suggest that high reputation VCs are able to select younger firms with better growth prospects than low reputation VCs.

Panels B, C, and D present the results on total production costs, materials costs, and labor costs respectively. In panels B and C we find that production and materials costs are consistently lower for high reputation VC backed firms compared to low reputation VC backed firms both before and after receiving VC financing, even though they are significantly above that of non-VC backed firms. Moreover, the increase in production and materials costs 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 decreases in the cost structure 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 costs for high reputation VC backed firms is on average around 2% in the first 4 years after receiving financing and around 4% in years 5 and after, which are both statistically and economically significant. A similar pattern also holds for materials costs in panel C. In the case of labor costs, presented in panel D, the pattern is somewhat different, though the increase in labor costs is also lower for high reputation VC backed firms compared to low reputation VC backed firms. Both prior to receiving financing and in the first four years after receiving financing, total labor costs are higher for high reputation VC backed firms, which could signify higher reputation VCs employing more skilled labor as suggested by Hellman and Puri (2002). However, as mentioned previously, the increase in such costs subsequent to financing is lower for the high reputation VC backed firms, again suggesting that better monitoring by high reputation VCs may be the reason for such costs to be in check, leading to more efficiency gains for such firms. Panel E presents the results on total employment which shows that both prior to VC financing and also in the first 4 years after receiving financing, total employment is higher for high reputation VC backed firms compared to low reputation VC backed firms, however the increase in employment from before receiving VC financing to after is not statistically different between the high and low reputation VC backed firms. Finally, panel F presents the results on capital expenditure or investments made by high and low reputation VC backed firms compared to non-VC backed firms. The results show that high reputation VC backed firms on average have lower capital expenditures than low reputation VC backed firms at all times, both prior to and after receiving VC financing. Moreover, the decrease in capital expenditures is also greater for high reputation VC backed firms from before to after receiving financing, suggesting that high reputation VCs may be potentially choosing firms that already have a better production infrastructure in place.

The results presented in this section clearly shows 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 are 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 compared to low reputation VC backed firms. 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.

5 Impact of Screening and Monitoring on the Probability of Exit

In this section, our goal is to present evidence regarding the relative impact of screening and monitoring activities of VCs on the exit probability of VC backed firms. We relate the operating efficiency or the TFP of a firm to its probability of exit either through an IPO or through a merger and acquisition as opposed to a write-off. 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). In doing so, we explicitly account for the different rounds of VC financing and its effect on subsequent TFP growth since future TFP growth is potentially endogenous to the amount of financing received by the firm.[37] We implement this using a two-stage instrumental variables approach; in the first stage we account for the endogeneity between future TFP growth and additional future rounds of VC investment received by the firm and predict the future TFP growth of the firm using the following regression.

$$Post\_TFP\_Gr_{it} = \alpha + \beta_1 pre\_VC\_TFP_{it} + \beta_2 Ln\_Round\_Amt_i + \gamma X_{i,t-1} + \varepsilon_{it} \tag{12}$$

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, Ln_Round_Amt denotes the amount of investment made by VCs in future rounds, and X_{it} is a set of firm and industry specific control variables. We then predict the future TFP growth of firms from this regression and use this $predicted\_post\_round\_TFP\_gr$ as an additional regressor in our second stage regression. Intuitively, this predicted TFP growth captures the growth in the productivity of the firms that can be attributed to the monitoring services provided by the VC. We then estimate the second stage using a multinomial logit model.

[37] The intuition here is straightforward. Even though TFP is independent of the scale of production, i.e., there is no direct effect of additional investment on TFP (since TFP is computed as the residual of a regression) it could be argued that future TFP is potentially endogenous to the level of monitoring of the VC. Under the assumption, that the VC will engage in more monitoring when he has greater amount of investment in the firm, one can argue that future TFP growth and additional round investments are endogenously determined. Further, it is also straighforward that TFP in prior years affects future round investments by VCs in the firm.

$$Exit\_Type = F\,(predicted\_post\_TFP\_gr,\ pre\_VC\_TFP,\ Firm\_size,\ VC\_reputation,\ Controls) \tag{13}$$

where $Exit\_Type$ is a dummy variable representing 3 categories, write-offs (the base category), M&As, and IPOs. In addition to firm size, we also control for several firm and industry specific variables that may affect the choice of the exit strategy of the firm. Further, we also compare if the exit strategy varies between firms backed by high and low reputation VCs, by estimating equation (13) separately for both VC reputation categories. Our results for (12) and (13) are presented in tables 11 and 12 respectively.

Table 11 presents the results for the first stage, which shows that pre_VC_TFP is negatively related to future TFP growth, implying that firms that have a lower level of TFP prior to receiving VC financing are the ones that experience larger TFP growth after receiving such financing. Additionally, both firm size and round amount is positively related to future TFP growth, while the Herfindahl index is negatively related to future TFP growth. We then predict $Post\_Round\_TFP\_Gr$ from this first stage regression and use it in our second stage. Results from our second stage are presented in panel A of Table 12, with the first set of results for the overall sample followed by our split-sample analysis of high reputation and low reputation VC backed firms respectively. Our results uncover several interesting facts. For the overall sample, we find that TFP of firms attributed to both screening and monitoring activities of VCs positively affect the probability of exit through an IPO as well as through an M&A, with the economic impact being greater for the IPO than for the M&A. In addition, we also find that round number and Herfindahl index are also positively related to the probability of a successful exit either through an IPO or an M&A. Not surprisingly and consistent with prior literature, our VC reputation variable is only significant for an exit through an IPO. Moreover, from the economic significance of these impacts, which are presented in panel B, we find that for each category of exit, the marginal impact on exit due to improvements in TFP resulting from monitoring is somewhat larger than the corresponding impact from screening, with the effects being more pronounced for exits through M&As than through IPOs. For example, a one standard deviation increase in TFP growth due to monitoring results in a 14% increase in the probability of an exit through an M&A, while a similar increase in the TFP due to screening only results in an increase of 9.4% in the probability of an exit through an M&A.

Finally, we separate out these effects for firms backed by high and low reputation VCs. Our results show that TFP improvements due to screening and monitoring are only statistically significantly related to an exit through an IPO for high reputation VC backed firms only. The economic significance of the effects provides us with more intuition. We find that for high reputation VC backed firms the impact of both screening and monitoring on an exit through an IPO is huge, a one standard deviation increase in these variables lead to an increase in the probability of an IPO by about 25.2% (for monitoring) and 23.5% (for screening). For an exit through an M&A, the impact is roughly about half that of an IPO; a one standard deviation increase for TFP growth due to monitoring leads to an increase in the probability of an M&A of about 11%, while it is 7.5% for screening. For low reputation VC backed firms we find no economic significance on either monitoring or screening for an exit through an IPO, correctly suggesting that such firms are probably not likely to exit through an IPO. However, we do find an economically meaningful impact of monitoring on the probability of an exit through an M&A for low reputation VC backed firms, which is approximately 16%. For such firms the impact of screening on the probability of an exit through an M&A is approximately 10%.

Overall, our results from this section suggest that the impact of monitoring and screening on a successful exit varies greatly depending on VC reputation as well as the choice of the exit strategy. Firms backed by high reputation VCs are more likely to exit through an IPO rather than an M&A consistent with the findings in Megginson and Weiss (1991), and both monitoring and screening by such VCs have nearly equal impacts on the probability of an exit through an IPO. Firms backed by low reputation VCs are much more likely to exit through an M&A and better monitoring by such VCs make this outcome even more likely. Finally, monitoring also has an impact on the probability of an exit through an M&A for high reputation VC backed firms, but it is around 5% lower than the probability of an exit through an M&A for a low reputation VC backed firm.

6 Conclusion

Using a unique sample from the Longitudinal Research Database (LRD) of the U.S. Census Bureau, we study several related questions regarding the efficiency gains generated by venture capital (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 (higher reputation versus lower reputation) better at generating such efficiency gains than others? Second, how are such efficiency gains generated: Do venture capitalists 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 time 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 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. On average, VCs select firms that have higher TFP of around 6% compared to non-venture 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 the VCs. Both these effects are economically significant, resulting in an increase in profits of approximately 21% and 35% respectively. Third, the above increase in efficiency of VC backed firms relative to non-VC backed firms is monotonically increasing over the four years subsequent to the year of initial VC financing, and continues till exit. Fourth, while the efficiency of firms prior to VC financing is similar across higher and lower reputation VC backed firms, the increase in efficiency subsequent to financing is significantly higher for the former firms, consistent with higher reputation VCs having greater monitoring ability. Our results indicate that this difference in monitoring ability between high and low reputation VC backed firms results in TFP improvements that are 10% greater for high reputation VC backed firms, which is economically very significant as it implies an increase in profits of approximately 35%. Fifth, the efficiency gains generated by VC backing arise primarily from improvement in product market performance (sales); however for high reputation VCs, the additional efficiency gain arises from both an additional improvement in product market performance as well as from reductions in various input 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. Firms backed by high reputation VCs are more likely to exit through an IPO rather than an M&A and both monitoring and screening by such VCs have nearly equal impacts on the probability of an exit through an IPO. Firms backed by low reputation VCs are more likely to exit through an M&A and better monitoring by such VCs make this outcome even more likely.

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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. The sample period is from 1972 to 2003.

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 non-VC backed firms in the manufacturing section (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 is the number of years since the firm first appeared in the LRD sample. 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 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. Firm Market share is the firm's market share in terms of sales in the same 3 digit SIC industry. Quasi-medians are the average of the 43rd and the 57th percentile for each variable. All the observations are firm-year observations. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively. Statistical significances for means and quasi-medians correspond to the t-test and sign-test, respectively. Statistical significance for mean and quasi-median differences correspond to t-tests and rank-sum tests, respectively.

		Venture Backed Firms	Non Venture Backed Firms	Difference
Total Assets	Mean	402577.37***	7944.79***	394632.58***
	Quasi-Median	16930.39***	435.40***	16494.99***
	Observations	16824	771830	
Total Sales	Mean	1035037.90***	23662.78***	1011375.10***
	Quasi-Median	65306.18***	3554.35***	61751.83***
	Observations	16824	771830	
Total Employment	Mean	5734.12***	178.43***	5555.69***
	Quasi-Median	588.50***	44.00***	544.50***
	Observations	16824	771830	
Materials Cost	Mean	478551.40***	12048.03***	466503.36***
	Quasi-Median	24117.50***	1404.50***	22713.00***
	Observations	16824	771830	
Salaries and Wages	Mean	157287.81***	3878.13***	153409.68***
	Quasi-Median	13704.50***	892.00***	12812.50***
	Observations	16824	771830	
Firm Age	Mean	16.39***	9.93***	6.46***
	Quasi-Median	16.00***	5.50***	10.50***
	Observations	16824	771830	
Firm Age at VC Financing	Mean	10.380***		
	Quasi-Median	8.167***		
	Observations	1503		
High Tech. Firm	Mean	0.324***	0.050***	0.274***
	Observations	16824	771830	
Industry Risk	Mean	3454.66***	1914.21***	1540.45***
	Quasi-Median	1641.86***	934.97***	706.89***
	Observations	16501	762440	
Firm Market Share	Mean	0.036***	0.002***	0.034***
	Quasi-Median	0.003***	0.000***	0.003***
	Observations	16791	769328	

Table 3: Univariate TFP Comparisons for VC backed and non-VC backed firms

Panel A reports univariate comparisons of TFP for VC and non-VC backed firms, and for the change in TFP from before to after the first round of VC financing for VC backed firms. Panel B reports univariate comparisons of TFP for high and low reputation VC backed firms. "*Before VC Financing*" includes all years prior to VC backing including the year of VC backing. "*After VC Financing*" includes all years subsequent to the year of VC backing. Statistical significances for means and medians correspond to t-tests and sign-tests, respectively, for the null hypothesis that the sample mean and median is equal to 0. Statistical significances for differences in means and medians correspond to t-tests and rank-sum tests. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively, for tests of means. $^{+++}$, $^{++}$, and $^{+}$ represent statistical significance at the 1, 5, and 10 percent levels, respectively, for tests of medians.

Panel A: TFP Comparisons for VC and non-VC Backed Firms			
	VC Backed Firms: Before VC financing	Non VC Backed firms	Diff.
Mean	0.018***	-0.034***	0.052***$^{, +++}$
Observations	5955	511503	
	VC Backed Firms : After VC Financing	Non VC Backed firms	Diff.
Mean	0.037***	-0.034***	0.071***$^{, +++}$
Observations	7348	511503	
	Diff: TFP Change Over Time for VC backed firms		
Mean	0.019**		

Panel B: TFP Comparisons for High and Low reputation VC Backed Firms			
	High Reputation VC	Low Reputation VC	Diff.
Before VC Financing			
Mean	0.023**	0.007	0.016^{+++}
Observations	2395	3303	
After VC Financing			
Mean	0.051***	0.018***	0.033***$^{, ++}$
Observations	3820	3341	
	Diff: TFP Change Over Time for High Reputation VC Backed Firms	Diff: TFP Change Over Time for Low Reputation VC Backed Firms	
Mean	0.028**	0.011	

Table 4: TFP Dynamics around the First Round of VC Financing

This tables reports results for panel data regressions where the dependent variable is the TFP of a firm for a given year. The independent variables 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(≥ 5),* which equals 1 in or after year 5 of VC financing and 0 otherwise; *One, Two, and Three Year Lagged TFP* of the firm; *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 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

	(1)	(2)	(3)	(4)	(5)	(6)
VCAfter	0.121***					
	[0.030]					
VCBefore(-4,0)		0.068***	0.061***	0.058***	0.058***	
		[0.021]	[0.017]	[0.018]	[0.019]	
VCAfter(1,4)		0.120***	0.109***	0.105***	0.102***	
		[0.032]	[0.026]	[0.028]	[0.029]	
VCBefore(-4)						0.029
						[0.024]
VCBefore(-3)						0.083***
						[0.025]
VCBefore(-2)						0.064***
						[0.024]
VCBefore(-1)						0.031
						[0.027]
VCBefore(0)						0.083***
						[0.028]
VCAfter(1)						0.088***
						[0.033]
VCAfter(2)						0.095***
						[0.033]
VCAfter(3)						0.109***
						[0.033]
VCAfter(4)						0.121***
						[0.037]
VCAfter(≥ 5)		0.188***	0.160***	0.153***	0.152***	0.155***
		[0.042]	[0.031]	[0.032]	[0.033]	[0.034]
One Year Lagged TFP			0.250***	0.243***	0.234***	0.234***
			[0.004]	[0.004]	[0.005]	[0.005]
Two Year Lagged TFP				0.025***	0.060***	0.060***
				[0.004]	[0.004]	[0.004]
Three Year Lagged TFP					0.001	0.001
					[0.004]	[0.004]
Firm Size	-0.057***	-0.057***	-0.047***	-0.048***	-0.050***	-0.050***
	[0.003]	[0.003]	[0.003]	[0.003]	[0.004]	[0.004]
Herfindahl Index	-0.019	-0.018	-0.027	-0.009	-0.014	-0.014
	[0.020]	[0.020]	[0.019]	[0.021]	[0.025]	[0.025]
Firm Fixed Effects	Y	Y	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y	Y	Y
Observations	524806	524806	399454	303838	226523	226523
Adjusted R-Square	0.414	0.414	0.49	0.508	0.522	0.522

Panel B: TFP Change Over Time

	(1)	(2)	(3)	(4)	(5)	(6)
VCAfter(1,4) - VCBefore(4,0)		0.052**	0.048**	0.047**	0.044**	
		[0.021]	[0.019]	[0.020]	[0.021]	
VCAfter(≥ 5) - VCBefore(4,0)		0.119***	0.099***	0.095***	0.095***	
		[0.033]	[0.025]	[0.026]	[0.028]	
VCAfter(1) - VCBefore(1)						0.055*
						[0.029]
VCAfter(2) - VCBefore(1)						0.053*
						[0.029]
VCAfter(3) - VCBefore(1)						0.077***
						[0.030]
VCAfter(4) - VCBefore(1)						0.084***
						[0.032]
VCAfter(≥ 5) - VCBefore(1)						0.137***
						[0.036]

Table 5: TFP Dynamics around the First Round of VC Financing for High and Low Reputation VC Backed Firms

This tables reports results for panel data regressions where the dependent variable is the TFP of a firm for a given year. The regressions are segmented by the reputation of VC syndicate that provides the first round of VC financing. VC reputation is High if the average market share of the VC syndicate, based on the amount raised by the VC over a five year period prior to the date of VC financing, is higher than the sample median and Low otherwise. 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; *One, Two, and Three Year Lagged TFP* of the firm; *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. 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.

Specification 1

	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***	
	[0.002]	[0.002]	[0.001]	
VCAfter(1,4)	0.174***	0.089***	0.085***	0.096***
	[0.003]	[0.003]	[0.001]	[0.000]
VCAfter(≥ 5)	0.262***	0.139***	0.122***	0.133***
	[0.005]	[0.005]	[0.001]	[0.000]
Firm Size	-0.064***	-0.064***		
	[0.002]	[0.002]		
Herfindahl Index	-0.014	-0.015		
	[0.018]	[0.018]		
Year Fixed Effects	Y	Y		
Firm Fixed Effects	Y	Y		
Observations	517718	518147		
Adj. R-Square	0.413	0.413		

Specification 2

	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)	0.068***	0.069***	-0.001*	
	[0.002]	[0.002]	[0.001]	
VCAfter(1,4)	0.161***	0.067***	0.093***	0.095***
	[0.003]	[0.003]	[0.001]	[0.001]
VCAfter(≥ 5)	0.22***	0.122***	0.098***	0.100***
	[0.005]	[0.005]	[0.001]	[0.001]
One Year Lagged TFP	0.224***	0.221***		
	[0.005]	[0.005]		
Two Year Lagged TFP	0.056***	0.055***		
	[0.004]	[0.004]		
Three Year Lagged TFP	-0.004	-0.005		
	[0.004]	[0.004]		
Firm Size	-0.055***	-0.055***		
	[0.003]	[0.003]		
Herfindahl Index	-0.011	-0.008		
	[0.022]	[0.022]		
Year Fixed Effects	Y	Y		
Firm Fixed Effects	Y	Y		
Observations	222149	222464		
Adj. R-Square	0.521	0.520		

Table 6: Switching Regressions with Endogenous Switching for VC and Non-VC Backed Firms

This table reports the result of Heckman two-stage estimation. 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 this regression are*:* *Average 5 year prior TFP*, which is the average TFP over the last five years starting from the current year; *Capital Gains Tax Rate,* which is the capital gains tax rate in the current year; *AAA Spread,* which is the spread of AAA bonds over 5 year treasury bonds in 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 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 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 on 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 1998 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 this regression are the *Inverse Mills Ratio* from the first stage and all the independent variables from the first stage except for *Average 5 year prior TFP, Capital Gains Tax Rate,* and *AAA Spread.* 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.

First Stage		*Second Stage*		
Dependent Variable: VC Backing Dummy		*Dependent Variable: TFP Growth*		
			VC Backed Firms	Non-VC Backed Firms
Average 5 year prior TFP	0.102**	Inverse Mills Ratio	1.087***	3.223***
	[0.041]		[0.289]	[0.502]
Capital Gains Tax Rate	-0.009*	Firm Size	0.239***	0.014***
	[0.005]		[0.058]	[0.004]
AAA Spread	-0.124***	Herfindahl Index	-0.078	-0.012
	[0.034]		[0.198]	[0.026]
Firm Size	0.209***	Firm Age	-0.007**	-0.003***
	[0.011]		[0.004]	[0.001]
Number of Plants	0.005***	Firm Market Share	-0.136	-0.259***
	[0.001]		[0.167]	[0.087]
Herfindahl Index	0.276	Industry Risk	0.000	0.000
	[0.191]		[0.000]	[0.000]
Firm Age	-0.004**	Number of Plants	0.004***	0.002***
	[0.002]		[0.001]	[0.001]
Firm Market Share	0.053	High Tech. Firm	0.679***	0.07***
	[0.348]		[0.159]	[0.024]
Industry Risk	0.00001**	S&P 500 Returns	-0.059	0.01***
	[0.000]		[0.148]	[0.003]
High Tech. Firm	0.608***	80s Dummy	0.326***	0.019***
	[0.042]		[0.074]	[0.007]
S&P 500 Returns	0.187	90s Dummy	0.101	0.014
	[0.128]		[0.075]	[0.011]
80s Dummy	0.122	Bubble Dummy	0.461***	0.046***
	[0.081]		[0.137]	[0.015]
90s Dummy	0.009			
	[0.077]	Firm fixed effects	N	Y
Bubble Dummy	0.26**			
	[0.114]			
Observations	407379	Observations	393	308902
Chi sq.	1064.06	Adj. R-Square	0.080	0.417

Table 7: 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. Panel A 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 panel 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 latter actual and hypothetical TFP growths. 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. Panel B reports the differences in the TFP growth improvements between VC and non-VC backed firms. P-values for t-tests and rank-sum tests are reported in parentheses. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

	Actual TFP Growth for VC backed firms	TFP Growth for VC backed firms if they had not obtained VC financing	TFP Growth Improvement	Paired *t*-test	Sign-rank test
Mean	0.016	-0.076	0.092	(0.000)**	(0.000)***
Obs.	393	393			

	TFP Growth for non-VC backed firms if they had obtained VC financing	Actual TFP Growth for non-VC backed firms	TFP Growth Improvement	Paired *t*-test	Sign-rank test
Mean	-0.042	-0.029	-0.012	(0.000)***	(0.000)***
Obs.	308902	308902			

Table 8: Matched Sample Comparison of TFP Growth after VC Financing

Panel A of 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. 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 0. P-values for differences in means and medians correspond to paired t-tests and sign-rank tests. Panel B reports means and quasi-medians for matched firm adjusted *TFP Growth* and *Average 5 year prior TFP.* Matched firm adjusted values are calculated as the value of the statistic for the sample firm minus the value of the statistic for the matched firm. P-values for means and medians correspond to t-tests and sign-rank tests, respectively, for the null hypothesis that the sample mean and median is equal to the matched firm mean and median. P-values for differences in means and medians correspond to t-tests and rank-sum tests. ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A

		Sample	Matched	Diff.
TFP Growth	Mean	0.023***	-0.050	0.072***
	p-value	(0.010)	(0.239)	(0.008)
	Quasi-median	0.007***	-0.041	0.048***
	p-value	(0.009)	(0.962)	(0.007)
	Observations	442	442	
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	

Panel B

		High Reputation VC	Low Reputation VC	Diff.
Matched Firm Adjusted TFP Growth	Mean	0.118***	0.028	0.090
	p-value	(0.001)	(0.498)	(0.106)
	Quasi-median	0.088**	-0.002	0.090*
	p-value	(0.026)	(0.786)	(0.091)
	Observations	207	217	
Matched Firm Adjusted Average 5 year prior TFP	Mean	-0.014	0.022	-0.036
	p-value	(0.718)	(0.512)	(0.480)
	Quasi-median	0.008	0.027	-0.019
	p-value	(0.664)	(0.325)	(0.799)
	Observations	261	298	

Table 9: 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 costs, 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; *One, Two, and Three Year Lagged values* of the dependent variable; 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 Costs		Log Capital Exp.		Log Materials Cost		Log Sal. & Wages		Log Total Employment	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
VCBefore(-4,0)	0.147***	0.056***	0.113***	0.039*	0.152***	0.074	0.104***	0.037*	0.062**	0.023	0.031	0.007
	[0.032]	[0.019]	[0.036]	[0.022]	[0.051]	[0.057]	[0.037]	[0.022]	[0.028]	[0.017]	[0.029]	[0.018]
VCAfter(1,4)	0.220***	0.101***	0.180***	0.088***	0.118**	-0.01	0.182***	0.095***	0.112***	0.049**	0.063*	0.027
	[0.043]	[0.024]	[0.044]	[0.029]	[0.059]	[0.066]	[0.043]	[0.027]	[0.034]	[0.021]	[0.034]	[0.021]
VCAfter(≥ 5)	0.352***	0.165***	0.293***	0.138***	0.093	-0.033	0.224***	0.118***	0.103***	0.048**	0.025	0.01
	[0.051]	[0.025]	[0.049]	[0.029]	[0.060]	[0.069]	[0.049]	[0.029]	[0.039]	[0.024]	[0.042]	[0.025]
Firm Size	0.593***	0.365***	0.618***	0.391***	1.040***	1.176***	0.614***	0.377***	0.581***	0.363***	0.522***	0.336***
	[0.005]	[0.007]	[0.006]	[0.008]	[0.008]	[0.016]	[0.006]	[0.008]	[0.005]	[0.007]	[0.005]	[0.007]
One Year Lagged Value of		0.475***		0.440***		0.085***		0.454***		0.502***		0.505***
Dep. Variable		[0.008]		[0.007]		[0.005]		[0.008]		[0.009]		[0.007]
Two Year Lagged Value of		0.057***		0.068***		-0.017***		0.053***		0.043***		0.045***
Dep. Variable		[0.005]		[0.005]		[0.004]		[0.006]		[0.005]		[0.005]
Three Year Lagged Value of		-0.017***		-0.008**		-0.055***		-0.001		-0.025***		-0.019***
Dep. Variable		[0.004]		[0.004]		[0.003]		[0.004]		[0.004]		[0.004]
Year Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	546006	252432	545941	252004	552311	256944	541722	249294	546565	252883	545239	252297
Adj. R-Square	0.932	0.962	0.916	0.953	0.67	0.738	0.912	0.953	0.932	0.963	0.929	0.962

Panel B: Change in Dependent Variable Over Time

	Log Total Sales		Log Production Costs		Log Capital Exp.		Log Materials Cost		Log Sal. & Wages		Log Total Employment	
VCAfter(1,4) - VCBefore(4,0)	0.072***	0.045**	0.066**	0.050**	-0.035	-0.084	0.078***	0.057**	0.050**	0.026*	0.032	0.02
	[0.027]	[0.018]	[0.029]	[0.020]	[0.053]	[0.055]	[0.030]	[0.023]	[0.022]	[0.015]	[0.023]	[0.015]
VCAfter(≥ 5) - VCBefore(4,0)	0.205**	0.108***	0.180***	0.099***	0.059	-0.107*	0.120***	0.080***	-0.041	0.025	0.006	-0.003
	[0.037]	[0.021]	[0.036]	[0.022]	[0.057]	[0.064]	[0.038]	[0.026]	[0.031]	[0.019]	[0.033]	[0.021]

Table 10: 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, log production costs, log capital expenditure, log materials cost, log salaries and wages, and log total employment of a firm for a given year. The regressions are segmented by the reputation of VC syndicate that provides the first round of VC financing. VC reputation is High if the average market share of the VC syndicate, based on the amount raised by the VC over a five year period prior to the date of VC financing, is higher than the sample median and Low otherwise. 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; O*ne, Two, and Three Year Lagged values of the dependent variable* of the firm; 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)	Change over time relative to VCBefore(-4,0): Diff. (High -Low)
VCBefore(-4,0)	0.049***	0.059***	-0.010***	
	[0.002]	[0.003]	[0.001]	
VCAfter(1,4)	0.112***	0.109***	0.003***	0.014***
	[0.003]	[0.004]	[0.001]	[0.001]
VCAfter(≥ 5)	0.179***	0.187***	-0.008***	0.002***
	[0.006]	[0.006]	[0.001]	[0.000]
One Year Lagged Value of Dep.	0.456***	0.454***		
Variable	[0.008]	[0.008]		
Two Year Lagged Value of Dep.	0.053***	0.053***		
Variable	[0.004]	[0.004]		
Three Year Lagged Value of Dep.	-0.022***	-0.022***		
Variable	[0.003]	[0.003]		
Firm Size	0.372***	0.374***		
	[0.007]	[0.007]		
Year Fixed Effects	Y	Y		
Firm Fixed Effects	Y	Y		
Observations	246791	247075		
Adj. R-Square	0.960	0.960		

Panel B: Log Production Costs				
	High Reputation VC	Low Reputation VC	Diff. (High - Low)	Change over time relative to VCBefore(-4,0): Diff. (High -Low)
VCBefore(-4,0)	0.023***	0.053***	-0.030***	
	[0.002]	[0.003]	[0.001]	
VCAfter(1,4)	0.072***	0.121***	-0.049***	-0.019***
	[0.004]	[0.004]	[0.001]	[0.001]
VCAfter(≥ 5)	0.119***	0.193***	-0.073***	-0.043***
	[0.006]	[0.007]	[0.001]	[0.001]
One Year Lagged Value of Dep. Variable	0.417***	0.416***		
	[0.007]	[0.007]		
Two Year Lagged Value of Dep. Variable	0.06***	0.06***		
	[0.005]	[0.005]		
Three Year Lagged Value of Dep. Variable	-0.016***	-0.016***		
	[0.004]	[0.004]		
Firm Size	0.403***	0.404***		
	[0.007]	[0.007]		
Year Fixed Effects	Y	Y		
Firm Fixed Effects	Y	Y		
Observations	246366	246644		
Adj. R-Square	0.951	0.951		

Panel C: Log Materials Cost				
	High Reputation VC	Low Reputation VC	Diff. (High - Low)	Change over time relative to VCBefore(-4,0): Diff. (High -Low)
VCBefore(-4,0)	0.025***	0.048***	-0.023***	
	[0.003]	[0.003]	[0.001]	
VCAfter(1,4)	0.089***	0.119***	-0.030***	-0.007***
	[0.004]	[0.004]	[0.001]	[0.001]
VCAfter(≥ 5)	0.103***	0.167***	-0.064***	-0.041***
	[0.007]	[0.007]	[0.001]	[0.001]
One Year Lagged Value of Dep. Variable	0.431***	0.429***		
	[0.007]	[0.007]		
Two Year Lagged Value of Dep. Variable	0.045***	0.046***		
	[0.005]	[0.005]		
Three Year Lagged Value of Dep. Variable	-0.010***	-0.010***		
	[0.004]	[0.004]		
Firm Size	0.389***	0.391***		
	[0.007]	[0.007]		
Year Fixed Effects	Y	Y		
Firm Fixed Effects	Y	Y		
Observations	243662	243931		
Adj. R-Square	0.951	0.951		

Panel D: Log Salaries and Wages	High Reputation VC	Low Reputation VC	Diff. (High - Low)	Change over time relative to VCBefore(-4,0): Diff. (High -Low)
VCBefore(-4,0)	0.04***	-0.001***	0.041***	
	[0.002]	[0.002]	[0.001]	
VCAfter(1,4)	0.064***	0.031***	0.032***	-0.009***
	[0.003]	[0.003]	[0.001]	[0.001]
VCAfter(≥ 5)	0.049***	0.051***	-0.002*	-0.042***
	[0.005]	[0.005]	[0.001]	[0.000]
One Year Lagged Value of Dep.	0.485***	0.481***		
Variable	[0.008]	[0.008]		
Two Year Lagged Value of Dep.	0.041***	0.040***		
Variable	[0.005]	[0.005]		
Three Year Lagged Value of Dep.	-0.029***	-0.028***		
Variable	[0.003]	[0.003]		
Firm Size	0.372***	0.376***		
	[0.007]	[0.007]		
Year Fixed Effects	Y	Y		
Firm Fixed Effects	Y	Y		
Observations	247239	247516		
Adj. R-Square	0.961	0.961		

Panel E: Log Total Employment	High Reputation VC	Low Reputation VC	Diff. (High - Low)	Change over time relative to VCBefore(-4,0): Diff. (High -Low)
VCBefore(-4,0)	0.019***	-0.014***	0.032***	
	[0.002]	[0.002]	[0.001]	
VCAfter(1,4)	0.037***	0.008**	0.029***	-0.003
	[0.003]	[0.003]	[0.001]	[0.001]
VCAfter(≥ 5)	0.003	0.014***	-0.011***	-0.043***
	[0.005]	[0.005]	[0.001]	[0.000]
One Year Lagged Value of Dep.	0.486***	0.482***		
Variable	[0.006]	[0.006]		
Two Year Lagged Value of Dep.	0.042***	0.042***		
Variable	[0.004]	[0.004]		
Three Year Lagged Value of Dep.	-0.024***	-0.024***		
Variable	[0.004]	[0.004]		
Firm Size	0.350***	0.354***		
	[0.006]	[0.006]		
Year Fixed Effects	Y	Y		
Firm Fixed Effects	Y	Y		
Observations	246656	246932		
Adj. R-Square	0.960	0.959		

Panel F: Log Capital expenditure

	High Reputation VC	Low Reputation VC	Diff. (High - Low)	Change over time relative to VCBefore(-4,0): Diff. (High -Low)
VCBefore(-4,0)	0.033***	0.115***	-0.082***	
	[0.008]	[0.009]	[0.003]	
VCAfter(1,4)	-0.077***	0.08***	-0.156***	-0.074***
	[0.012]	[0.013]	[0.004]	[0.002]
VCAfter(≥ 5)	-0.067***	0.031	-0.098***	-0.016***
	[0.020]	[0.021]	[0.003]	[0.001]
One Year Lagged Value of Dep.	0.074***	0.073***		
Variable	[0.004]	[0.004]		
Two Year Lagged Value of Dep.	-0.02***	-0.021***		
Variable	[0.003]	[0.003]		
Three Year Lagged Value of Dep.	-0.058***	-0.059***		
Variable	[0.003]	[0.003]		
Firm Size	1.227***	1.229***		
	[0.015]	[0.015]		
Year Fixed Effects	Y	Y		
Firm Fixed Effects	Y	Y		
Observations	251271	251551		
Adj. R-Square	0.725	0.723		

Table 11: Effect of VC Screening and Monitoring on Probability of Exit: First Stage

This table reports the results of an OLS regression with *Post-Round TFP Growth,* which is the difference between the average TFP between the current and subsequent VC financing round and the average TFP between the current and previous VC financing round, as the dependent variable. The independent variables are *Average Pre-VC Financing TFP*, which is the five year average TFP prior to obtaining VC financing; *Log of Round Amount,* which is the natural log of the round amount (in dollars); *Round Number*, which is the number of the current round; *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 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; *High Reputation VC,* which is a dummy that takes the value 1 if the average market share of the VC syndicate (based on the amount raised by the VC over a five year period prior to the date of VC financing) is higher than the sample median and 0 otherwise; *Industry risk*, which is 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; *Firm Age*, which is the number of years since the firm first appeared in the LRD sample; *High Tech. Firm,* which is a dummy variable that takes the value 0 if the firm's three-digit SIC code is 357, 366, 367, 372, 381, 382, or 384; *S&P 500 Returns*, which is the return on the S&P 500 index in a given year; *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 1998 and 2000, and 0 otherwise. 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.

Dependent Variable: Post-Round TFP Growth	
Average Pre-VC Financing TFP	-0.295***
	[0.032]
Log of Round Amount	0.019**
	[0.009]
Round Number	-0.022
	[0.015]
Firm Size	0.014*
	[0.008]
Herfindahl Index	-0.405***
	[0.116]
Firm Market Share	-0.07
	[0.152]
High Reputation VC	0.022
	[0.025]
Industry Risk	0.000
	[0.000]
Firm Age	-0.001
	[0.002]
High Tech. Firm	0.044
	[0.031]
S&P 500 Returns	0.268*
	[0.113]
80s Dummy	-0.040
	[0.035]
90s Dummy	-0.024
	[0.048]
Bubble Dummy	-0.066
	[0.077]
Adj. R-Square	0.1535
Observations	657

Table 12: Effect of VC Screening and Monitoring on Probability of Exit: Second Stage (Multinomial Logit)

Panel A of 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, *Predicted Post-Round TFP Growth*, which is the predicted value of Post-Round TFP Growth estimated from the regression in Table 9; *Average Pre-VC Financing TFP*, which is the five year average TFP prior to obtaining VC financing ; *Log of Round Amount,* which is the natural log of the round amount (in dollars); *Round Number*, which is the number of the current round; *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 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; *High Reputation VC,* which is a dummy that takes the value 1 if the average market share of the VC syndicate (based on the amount raised by the VC over a five year period prior to the date of VC financing) is higher than the sample median and 0 otherwise; *Industry risk*, which is 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; *Firm Age*, which is the number of years since the firm first appeared in the LRD sample; *High Tech. Firm,* which is a dummy variable that takes the value 0 if the firm's three-digit SIC code is 357, 366, 367, 372, 381, 382, or 384; *S&P 500 Returns*, which is the return on the S&P 500 index in a given year; *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 1998 and 2000, and 0 otherwise. The regression is also separately estimated for firms that are backed by high reputation VCs in the first round and for firms that are backed low reputation VCs in the first round. Panel B reports change in the probability of exit for a one standard deviation increase in *Predicted Post-Round TFP Growth* and *Average Pre-Round TFP.* 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.

Panel A: Multinomial Logit Estimation Results, Dependent Variable: Type of Exit, Base Outcome: No Exit

	Overall		High Reputation VC Backed		Low Reputation VC Backed	
	IPO	M&A	IPO	M&A	IPO	M&A
Predicted Post-Round TFP Growth	7.954**	5.563**	11.005**	6.474	4.297	4.879
	[3.432]	[2.551]	[4.748]	[3.986]	[5.186]	[3.188]
Average Pre-VC Financing TFP	2.315**	1.384*	3.195**	1.685	1.274	1.079
	[1.062]	[0.824]	[1.387]	[1.247]	[1.741]	[1.092]
Round Number	0.474***	0.325***	0.677***	0.296*	0.041	0.356**
	[0.140]	[0.123]	[0.178]	[0.173]	[0.232]	[0.167]
Firm Size	0.012	0.087	-0.018	0.113	0.036	0.029
	[0.098]	[0.070]	[0.131]	[0.111]	[0.166]	[0.091]
Herfindahl Index	4.69**	2.694*	6.676***	3.351	0.562	2.112
	[1.835]	[1.468]	[2.343]	[2.243]	[3.258]	[1.925]
Firm Age	0.008	0.005	-0.016	-0.024	0.037	0.032
	[0.022]	[0.016]	[0.028]	[0.025]	[0.036]	[0.023]
High Reputation VC	0.773**	0.143				
	[0.351]	[0.274]				
High Tech. Firm	0.343	0.077	-0.229	-0.158	1.085**	0.197
	[0.384]	[0.287]	[0.520]	[0.435]	[0.539]	[0.396]
S&P 500 Returns	-2.282**	-1.627*	-2.097	-0.365	-2.278	-2.788**
	[1.160]	[0.905]	[1.561]	[1.366]	[1.848]	[1.189]
80s Dummy	1.478***	1.737***	1.849***	1.994***	0.711	1.447**
	[0.540]	[0.407]	[0.653]	[0.486]	[0.861]	[0.701]
90s Dummy	1.254**	1.664***	1.326*	1.905***	0.962	1.411*
	[0.639]	[0.472]	[0.798]	[0.617]	[1.008]	[0.760]
Bubble Dummy	0.319	0.848	1.111	0.418	-33.872***	0.839***
	[0.799]	[0.663]	[0.926]	[0.894]	[1.192]	[0.997]
Chi-Sq.	67.10		50.02		9469.02	

Panel B: Predicted Probability Change for a One Standard Deviation Increase in the Independent Variable

	Overall		High Reputation VC Backed		Low Reputation VC Backed	
	IPO	M&A	IPO	M&A	IPO	M&A
Predicted Post-Round TFP Growth	0.124	0.14	0.252	0.111	0.004	0.159
Average Pre-VC Financing TFP	0.113	0.094	0.235	0.075	0.003	0.099