# Venture Capital and Industrial "Innovation"

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For the sample period of 1965-1992, Kortum and Lerner (2000) find that venture capital ("VC") investment has a positive impact on patent counts at the industry level, and that this impact is larger than that of R&D expenditures. We confirm that this positive impact continued to be present and became even stronger in late 1990s during which VC industry experienced an unprecedented growth. We then proceed to study whether this positive impact of VC is also present on productivity growth, which is a measure of innovation alternative to patent counts. Unlike the impact on patent counts, we do not find that VC investment affects total factor productivity growth. We do find that VC investment is positively associated with labor productivity but this positive impact is originated from the technology substitution from labor to other productive inputs such as energy and material. Therefore, our finding suggests that, at the industry level, VC investment increases the patent propensity but may not necessarily improve the productive efficiency. Various interpretations are offered as to why this may be the case.

**Keywords:** Venture Capital, Patent, Productivity, Innovation, Factor Substitution.
**JEL Classifications:** G24, D24, L26, O31, O32.

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# 1 Introduction

Using industry level data, Kortum and Lerner (2000) find that venture capital ("VC") investments are more effective than R&D in generating patents, and conclude that "While the ratio of VC to R&D averaged less than 3% from 1983-1992, our estimates suggest that VC may have accounted for 8% of industrial innovations in that period." It is worthwhile to re-examine this claim for the following two reasons. First, the U.S. VC industry experienced an explosive growth during late 1990s that Kortum and Lerner (2000) did not include in their sample. Given that some characterize this period as NASDAQ bubble (e.g. Shiller, 2000; Ofek and Richardson, 2003), it is interesting to study whether VC investment during this "bubble" period continued to be as productive in generating patents as before. Second, measuring technological innovation is a difficult task[1] and such a task would better be done from multiple perspectives, instead of using patent only. Reinforcing our concern, many authors recently raised questions as to the use of patents as a measure of innovation. For instance, Jaffe and Lerner (2004) document how recent changes in patenting - an institutional process that was created to nurture innovation - have wreaked havoc on innovators, businesses, and economic productivity. Allison et al. (2003) claim that many patents are not worth enforcing because the inventions they cover turn out to be worthless.

In this paper, we begin with extending the sample period to 2001 in order to study the impact of VC investment on innovations during the NASDAQ bubble period. This extension presented two challenges. First, Venture Economics data that Kortum and Lerner (2000) use sparsely record SIC codes of VC-backed companies after 1992. Therefore, we handcollect the information, and for the observations with which we cannot determine SIC codes, we assign the weights for each SIC code using the bridge table between SIC and VEIC we develop. Second, the NBER manufacturing

[1] Acs and Audretsch (2005) summarize measures of technological change as (1) a measure of the inputs into the innovative process, such as R&D expenditures; (2) an intermediate output, such as the number of inventions which have been patented; or (3) direct measure of innovative output (such as productivity growth).

database that contains comprehensive productivity information was discontinued in 1997, and we extend this database by gathering information from multiple sources, in the same way as the NBER database was constructed.[2] Our final data consist of an annual panel of nineteen U.S. manufacturing industries between 1968 and 2001.

To maintain the comparability of our work against Kortum and Lerner, we adopt the same empirical model as theirs, which is specified as a linearized patent production function with two inputs, namely, R&D and VC investment. To lessen the bias caused by omitting unobservable technological opportunity from the regressions, instrumental variables are used.

Confirming the results of Kortum and Lerner (2000), we find that VC investment continued to be a highly effective driver of patent activities even during late 1990s. Further, the relative power of VC investment to R&D in explaining patent counts increases by including this period, suggesting that VC money during this period was not necessarily invested to support less "innovative" businesses than during other periods. Our result contrasts with Gompers and Lerner (2003). Studying the same sample as Kortum and Lerner (2000), Gompers and Lerner (2003) find that the relative power of VC investment to R&D in explaining patent counts decreases during the boom periods in which the amount of VC investment is high.

We then proceed to use, instead of patent counts, total factor productivity ("TFP") growth and labor productivity growth to see whether the results using patents also hold for these alternative measures of innovations. Unlike the results on patent, we do not find that VC investment significantly and positively affects TFP growth. We do find that VC investment positively affects labor productivity growth. Nevertheless, this positive impact is due to the technology substitution using more energy and material and less labor in VC-intensive industries. In summary, our empir-

[2] The NBER-CES Manufacturing Industry Database was extended up until 2005 recently; see the web page (http://www.nber.org/data/nbprod2005.html) for details. We re-estimate all the regressions using both the SIC- and NAICS-based extended data sets, and qualitatively very similar results are confirmed (although unreported).

ical results suggest a possibility that VC investment does increase patent propensity but may not necessarily increase TFP - a classic measure of innovation.

We examine the possibility that VC investment may motivate established firms to strategically patent low-quality innovations. We do not find that the quality of patents owned by established firms decline as VC investment increases. Instead, we find that the "originality" of these patents is positively related with VC investment. Simply speaking, the patent originality measure is the breadth of knowledge on which the patent is based. Therefore, our finding suggests that established firms draw their knowledge from a broader source when their industries are experiencing high VC activity. Our finding is related with Dushnitsky and Lenox (2005) who find that established firms may not enjoy attractive financial returns from their corporate venture programs but may benefit by accessing new technology through their portfolio firms and broadening their knowledge bases, which are reflected into the subsequent increase in patenting of the established firms.

Similar to this paper, many authors study the impact of VC investment on innovation.[3] In addition to the aforementioned finding at the industry level, Kortum and Lerner (2000) find that patents granted to VC-backed companies are cited more often than other patents, suggesting that VC-backed companies are engaged in important innovative activities. Hellmann and Puri (2000) find that VC-backed firms follow more innovative strategies than non-VC-backed firms. Using German data, Tykova (2000) finds the positive relation between VC investment and patent application, similar to Kortum and Lerner (2000). One problem of these results is that they do not distinguish which way the causality runs. Does VC investment makes the invested firms innovative, or do innovative firms receive VC investment?

A few paper address this causality issue by studying innovative activities after VC investments.

[3]Some papers study the impact of VC on firm-level growth, Hellmann and Puri (2000) and Engel (2002) find that VC-backed firms grow faster than their industry counterparts. Rapid growth also characterizes VC-backed firms in Japan (Suzuki, 1996).

Zucker, Darby, and Brewer (1998), who studied causes of biotechnology start-up firms. Interestingly, they find that controlling for the presence of local star scientists the historical size of VC market negatively affects the rate of biotechnology start-up. Katila and Shane (2005) study whether licensed MIT patents are commercialized. They find that the patents are more likely to be commercialized if the licensee firms are in the industry with high VC investment. Nevertheless, puzzlingly they find that this effect exists only for established firms but not for new firms. Studying the sample of German firms, Engel and Keilbach (2007) examine whether firms with patents attract VC investment or VC investment aids firms to patent in the future. By finding twin firms, one of which is VC-funded and the other is not, they report that VC-funded firms register more patents than their twins before receiving VC investment, whereas this tendency disappears after the investment is made. Therefore, this result suggests that patents stimulate VC investment but not the other way around. Studying the sample of firms that went to public in the Italian Stock Exchange between 1995 and 2004, Caselli, Gatti and Perrini (2009) find the same result as Engel and Keilbach.[4]

As with this paper, a few papers study the impact of VC investment on TFP growth. Romain and van Pottelsberghe (2004) find that VC investment enhances both absorptive capacity and productivity more than R&D does for the country level panel data. Tang and Chyi (2008) find that through its role of an internal diffusion channel of knowledge, VC industry promotes TFP growth in manufacturing industries in Taiwan. Nevertheless, using VAR for the U.S. manufacturing industry data, Hirukawa and Ueda (2011) find that the correlation between TFP and VC investment may be driven by the opposite causality - productivity growth drives VC investment. Studying a sample of VC-backed manufacturing firms that appear in the Census data, Chemmanur, Krishnan and Nandy (2011) find that VC-backed firms have higher TFP than non-VC-backed firms at the time

[4]Stuck and Weingarten (2005) contend that VC thwarts innovations and their portfolio firms more business oriented, as VC's general partners often possess advanced business degrees but not science degrees.

of initial VC funding as well as experience a higher TFP growth than non-VC-backed firms after VC funding.

**Organization of the Paper** The rest of the paper is organized as follows: Section 2 describes the data used in this paper. The details in constructing new data sets are also discussed. Section 3 presents the results of empirical analyses. Section 4 discusses and studies a possible impact of VC investment on patent propensity. Section 5 concludes. For simplicity, in what follows, we refer to Kortum and Lerner (2000) as "KL."

# 2 Data Description

In this section, we describe how we construct the data set for our empirical analysis. Our data are annual and consist of VC disbursement, R&D expenditures, patent count, and productivity growth. Each item is aggregated to 19 U.S. manufacturing industries that roughly correspond to 2-digit SIC codes (see Table 2 for details) and the sample period is from 1968 to 2001.[5] There are two major challenges in assembling this data set. The first challenge is concordance between the VC data and the TFP data. The second challenge is extending the TFP data beyond the NBER coverage.

## 2.1 Data Sources

The data analyzed in this paper come from the following four main sources: VentureXpert, Bertelsman, Becker, and Gray's NBER-CES Manufacturing Industry Database ("the NBER productivity database"), the NBER U.S. Patent Citations Data File ("the NBER patent database"), and Funds

[5] There are two differences in the sample coverage between this paper and KL. First, the sample period of KL starts three years earlier than ours. This is because computation of our TFP growth requires the data on employees' social security contribution and fringe benefit, which is not available before 1968. Second, we do not include "Other manufacturing," which exists in KL. The reason why we do not include this industry stems from the transition from SIC to NAICS in 1997. "Other manufacturing" includes SIC 27 (Printing and Publishing), which was excluded from the manufacturing industries under NAICS. As a result, Annual Survey of Manufacturers stopped collecting data in this sector, and we were not able to extend the productivity series in "other manufacturing" beyond 1997.

for Industrial R&D Performance, by industry and by size of company: 1953–98 from National Science Foundation ("the R&D database").

VentureXpert is a proprietary database of Venture Economics, which is a division of Thomson Financial. Venture Economics receives quarterly reports from VC organizations and from major institutional investors on their portfolio holdings and, in exchange, provides summary data on investments and returns. VentureXpert reports daily VC investment data from 1960 to date. VentureXpert records SIC codes of VC-backed firms fairly well up to 1992, but only sparsely after 1992. We therefore gather this SIC information in the way described later.

The NBER productivity database draws original data from the Bureau of Census and contains productivity related variables for all manufacturing industries at the SIC 4-digit level.[6] The data are annual, start from 1958 and end in as early as 1996. We improve the NBER productivity database by adding the employer's social security contribution and fringe benefit to payroll. These two items consist a significant portion of employers' labor cost, and it's importance has grown over the last two decades. For instance, they accounted for 10.8% of total payroll in 1968 and grew to 21% in 2001. Therefore, if we would ignore these two labor cost items, we would significantly underestimate labor shares and would likely underestimate productivity growth, because labor input growth is slower than growth of other inputs. In order to reflect the impact of rapid increases of VC investment in the recent years into our analysis, we extend the NBER productivity database up to 2001 in the method described in Hirukawa and Ueda (2011). Extensive productivity data are available only in this database and it covers only manufacturing. Thus, we limit our scope to manufacturing industries.

The NBER patent database and its extension contain[7] the information of utility patents granted

[6] Bartelsman and Gray (1996) give detailed descriptions about this NBER manufacturing database.

[7] The extension is downloadable from the Bronwyn Hall's website (http://elsa.berkeley.edu/users/bhhall/bhdata.html). This extension has the primary international classification which is not present in the original NBER patent database. We compile the patent data by SIC code using the concordance between the primary international classification

at U.S. patent and trademark office ("USPTO") from 1963 to 2002.[8] For our empirical analysis, we sort the patent data by year of application instead by year of grant. The NBER patent database and its extension do not cover all patents applied between 1963 and 2001 because it is customary to take more than a year before a patent is granted. Therefore, we also extract updated data from the patent bibliographic raw files at USPTO.[9]

The R&D database contains annual spending of R&D sorted by industry and by source of funding. The industry classification scheme roughly corresponds to the SIC 2-digit level. As the R&D database is not available in a finer industry classification, we are not able to go into finer classifications of industry. As KL do, we interpolate if numbers are missing due to the NSF's undisclosure policy.

## 2.2 Concordance

One complication involved in combining VentureXpert and the NBER database is industry concordance. VentureXpert has the data item called SIPC that records the primary 4-digit SIC codes of the VC financed companies. This data item is well recorded until 1992; among the 25,328 VC deals between 1965 and 1992, 21,182 (84%) observations record the information. After this period, among 42,003 VC deals between 1993 and 2001, only 4,146 (9.9%) deals record this primary SIC code. Instead of SIC codes, VentureXpert uses its own proprietary industry classification system, the Venture Economics Industry Code ("VEIC"). There is no missing record for this VEIC variable. Reflecting the industry focus of VC, some industries are classified in more detail and others are in less detail than under SIC. A single industry in VEIC may consist more than one industry in SIC and *vice versa*. Differences in terminology across the two databases add another difficulty. For

and SIC developed by Brian Silverman. (http://www.rotman.utoronto.ca/~silverman/ipcsic/documentation_IPC-SIC_concordance.htm)

[8] See Hall, Jaffe, and Trajtenberg (2001) for the details of these patent databases.

[9] http://www.uspto.gov/web/menu/patdata.html

instance, the distinction between manufacturing and service is not clear in VEIC. A firm classified in "Biotech Related Fine Chemicals" (VEIC 4311) may belong to "Chemicals and allied products" (SIC 2-digit, 28) or "Research, development, and testing services (except noncommercial research organizations)" (SIC 3-digit, 873). To maintain the comparability, we use the industry classification scheme same as the one used by KL.

KL aggregate 3-digit level SIC industries into 20 industries. The name of each industry and corresponding SIC codes are presented in Table 2. Hereafter, we call this industry classification system "KL classification." The NBER productivity database records data at the SIC 4-digit level that is finer than KL classification. We aggregate both TFP growth and labor productivity growth by averaging corresponding 4-digit figures weighted by value added. To construct VC investment data along with KL classification, we first fill the missing records of SIC using the SDC Platinum Global New Issue and CRSP through CUSIP match. We find the primary 4-digit SIC codes of the companies involved in 3,138 deals in this way. We then resort to handcollecting this data item. As our focus is on the manufacturing industries, we first exclude VC deals apparently involving non-manufacturing firms. To be concrete, we focus our handcollection effort on the observations whose VEIC are ever recorded together with the SIC codes 2000-3999 (manufacturing) in the entire VentureXpert database. We then use D&B Million Dollar Database and the business description written in VentureXpert to fill in SIC code. We handcollect the information for additional 4,353 observations.[10]

Then, we divide the data into two groups: the data points with which SIC codes are recorded and the ones with which SIC codes are not recorded. If the SIC code is recorded, we converted the SIC code into a KL classification code using the concordance given in Table 2. Subsequently

[10] We fill additional 481 observations by merging Venture Xpert data with CRSP through CUSIP, additional 2,657 observations by merging with Global New Issue through CUSIP, additional 3,909 observations from D&B Million Dollar Database, and 444 observations by reading the business description of the companies.

we assign 100% of investment amount of the record to the KL classification code into which the original SIC code was converted. If the SIC code is not recorded, the recorded VEIC is used to distribute the investment amount into SIC-based industries. The distribution rule is constructed from the data records with SIC codes and thereby KL classification assigned in the way described above. For each VEIC, we obtain the distribution of investment amount over KL classification codes and use the same distribution for assigning KL classification codes to each record without SIC codes. For instance, among data points with SIC codes, total of $202 millions are invested into Circuit Boards industry (VEIC 3140), $60 millions are invested in Office and Computing Machine (KL classification code, 13), $141 millions are invested in Communication and Electronic Industries (KL classification code, 15) and $1 million is invested in Professional and Scientific Instruments Industry (KL classification code, 19). For the data point that does not have SIC but is Circuit Boards Industry according to VEIC, we assign 60/202 of the investment amount to Office and Computing Machine, 141/202 of investment amount to Communication and Electronic Industries and 1/202 of investment amount to Professional and Scientific Instruments Industry.

### 2.3 Descriptive Statistics

Table 1 presents the summary statistics of the variables used in our empirical analysis. All figures are computed from the panel of 19 manufacturing industries. Table 2 shows VC investment classified into each industry using the method described above.

It is easy to observe that VC investments are clustered. In particular, Office and computing machines (KL 13), Communication and electronics (KL 15), and Professional and scientific instruments (KL 19) account for two thirds of the total VC investment in manufacturing industries to date. One can also see that VC investment in Office and computing machines and also Communication and electronic is not only large in absolute term but also in relative to R&D expenditures. Both TFP growth and labor productivity growth in this sector are also high. However, there is one caveat for interpreting these high numbers. One of the biggest problems to measure innovation by TFP growth is a difficulty in measuring quality improvement. Unlike cost-reducing innovation, to identify quality improvement requires detailed knowledge in assessing and measuring product quality. For this reason, TFP growth associated with quality improvement is infrequently incorporated. Computer related industries are rare ones that incorporate this TFP growth due to quality improvement more accurately than other industries. In 1980s, the Bureau of Census conducted the measurement of quality change in those industries with help of IBM. This is the only significant attempt made by the Bureau. For this reason, industries other than computer related ones may not exhibit substantial quality improvement in their TFP growth figure and it may be underrepresented.

Table 3 shows that VC investment in the U.S. manufacturing industry has dramatically grown during the last four decades. The amount of investment in the recent few years is about 100 times as much as the one in 1968-70. Notably, stimulated by a sequence of regulatory changes favorable to VC, the investment amount significantly increased from 1970s to 1980s. These changes involve the clarification of ERISA prudent man rule[11], the reduction of capital gains tax rate[12], and the introduction of Bayh-Dole Act[13] that facilitated technology transfers from universities to private sectors. The whole VC industry experienced a downturn in the early 1990s due to asset quality problems of pension funds. Those funds were pulled out from private equity investments to reduce riskiness of their portfolios. Pension funds are main financing sources for U.S. venture capitalists and this assets reallocation by pension funds severely hit venture capitalists. Table 3 also shows the rapid growth of patenting activities in 1990s, as documented by Kortum and Lerner (1998).

[11] In 1978, Department of Labor clarified that investments in VC funds by pension funds do not violate the prudent man rule in Employee Retirement Income Security Act ("ERISA").

[12] See Gompers and Lerner (1998) for details.

[13] Enactment of the Bayh-Dole Act (P.L. 96-517), the "Patent and Trademark Act Amendments of 1980", on December 12, 1980 created a uniform patent policy among the many federal agencies that fund research. Bayh-Dole enables small businesses and nonprofit organizations, including universities, to retain title materials and products they invent under federal funding. Amendments to the Act were also created to include licensing guidelines and expanded the law's purview to include all federally-funded contractors, (P.L.98-620).

Compared to the data used by KL, our VC investment figures are systematically larger except the year 1976, for which the number of firms receiving VC funding is 47 in KL (Table 1) and 44 in our sample (Table 3). This discrepancy may happen because Venture Economics backfills their database. If so, our results will be more subject to a survivorship bias than KL. This survivorship bias is likely to inflate the positive impact of VC investment on innovations because a higher fraction of older data points is investment made by successful and surviving VC funds, and their investments are likely to be higher quality than average. As we discuss later, our estimated coefficients on VC investment are higher than KL, and consistent with this backfilling story.

Table 4 shows the correlation between variables. Our TFP growth taking account for employers' social security contribution and benefits are highly correlated with the NBER TFP growth. Both early-stage and total VC investments are positively and significantly correlated with all five measures of innovation (NBER TFP growth, our TFP growth, labor productivity growth, and production labor productivity growth, and patent) as expected. Privately-funded R&D is also significantly related with these measures of innovation. Nevertheless, federally-funded R&D is not significantly related with any measures of innovation. This low correlation may be due to the following two reasons. First, federally sponsored research projects are more basic than applied in their natures, and therefore it takes long for the benefits of such research to be realized. Second, federally sponsored projects may have commercial values lower than that of company sponsored projects, as federal agencies have the motives different from profit-seeking. And therefore, innovations generated by federal funds may be less commercialized (including the process to patent innovations) than those generated by company funds.

## 3 Empirical Methods and Results

In this section, we present the methods and results of our empirical analysis. Underlying methods used here are the same as the instrumental variables method in KL. KL assume that the patent production function is of the form $P_{it} = \left(R_{it}^{\rho} + bV_{it}^{\rho}\right)^{\alpha/\rho} u_{it}$, where subscripts $i$ and $t$ denote industry and time, respectively, $P$ is patent count, $R$ is R&D expenditure, $V$ is VC investment, and $u$ is unobservable technological opportunities. KL estimate that $\rho$ is close to one and then focus on the linearized specification

$$\ln P_{it} = \alpha \ln R_{it} + \alpha b \left(V_{it}/R_{it}\right) + \ln u_{it}.$$

We also employ this linear specification. Similar to KL, our focus is $b$, which measures the power of VC investment in increasing innovation relative to that of R&D expenditures. Note that $\alpha$ is a return-to-scale parameter and it should theoretically be positive. If $u_{it}$ is correlated with observable explanatory variables, OLS estimate of coefficients on these variables are biased. Following KL, we use gross industry product as an instrument for $R_{it}$ and, as the instrument for $V_{it}/R_{it}$, the variable that is equal to zero before 1979 and from 1979 equal to the average $V_{it}/R_{it}$ over the period of 1968-1975 or 1968-1978. The latter instrument is motivated by the clarification of ERISA prudent man rule described in the previous section.

For all regressions presented below, we control for federally-funded industrial R&D, industry dummies and year (or period) dummies. We are also aware that both industry- and time- dimensions are not large in our data set: the sample size of our entire sample is $\#\{\text{industries}\} \times \#\{\text{years}\} = 19 \times 34 = 646$. Under this circumstance, it is unclear whether a particular covariance estimate provides a satisfactory approximation to its true value. Then, to conduct conservative inference, we calculate standard errors in two alternative ways for each parameter estimate and utilize them complementarily. As in KL, standard errors are computed based on the autocorrelation-consistent covariance estimator with maximum of three lags by Newey and West (1987). Besides, we obtain standard errors from the two-way cluster-robust covariance estimator across industry and time by Cameron, Gelbach and Miller (2011) and Thompson (2011). Tables 5-9 report the former in parentheses and the latter in brackets.

### 3.1 Patent Results

We begin with replicating the KL's instrumental variable regression models over the extended sample period. Our results are summarized in Table 5. In Panel A, we fix the coefficient on $\ln R_{it}$ to either 0.2 or 0.5, instead of estimating it. This is to lessen the concern that gross industry product may not be a good instrument. In Panel B, we instrument $R_{it}$ by gross industry product. In the first four columns of Panel B, the cutoff year for the instrument for the ratio of VC and privately-funded R&D is 1979 as described above. In the next four columns, the cutoff year is changed to 1976. For all specifications, we run the same regression for the two sample periods, 1968-2001 and 1968-1992. The latter sample period is almost identical to that of KL and the results of this restricted sample can help us to understand why our results are quantitatively different from KL as described below.

In sum, our results confirm that the KL's findings are robust to including the NASDAQ bubble period in the sample. In all specifications, the estimated coefficients on privately-funded R&D and the ratio of VC and privately-funded R&D are both positive and significant, the same as the KL's findings. Interestingly, our estimated coefficients on the ratio of VC and privately-funded R&D as well as on privately-funded R&D are substantially smaller when we drop 1993-2001 from our sample period. This indicates that the positive impact of VC investment on patent counts became larger in 1990s as well as the patent production function became less subject to decreasing return to scale.

Even after we restrict our sample period to 1968-1992, our estimated coefficients are all substantially bigger than those found in KL. This difference is pronounced if we use the number of firms receiving VC funding instead of venture disbursements. For instance, when they fix the coefficient on privately-funded R&D to 0.5, which corresponds to the right half of Panel A in our Table 5, KL's estimated coefficients on the ratio of VC and privately-funded R&D are 2.51 and 1.72, while our estimates are 10.25 and 2.10.[14] The survivorship bias our data are subject to may explain why our coefficients are bigger than theirs.

### 3.2 TFP Results

We now study the impact of VC investment on productivity growth. Instead of patent counts, we use TFP growth as a dependent variable expressed in percentage. Our results are presented in Table 6. The first two columns contain the result using OLS without instrumental variables. The third and fourth columns contain the results under the same specification as the patent regression instrumenting both privately-funded R&D and the ratio of VC and privately-funded R&D, in the same manner as KL. The estimated coefficients on the ratio of VC and privately-funded R&D are all positive in these first four regressions. Nevertheless, the standard errors of these coefficients are also large and it is hard to find evidence against the hypothesis that the ratio of VC and privately-funded R&D does not affect TFP growth.

To examine whether this insignificance result is robust, we include three additional control variables. First, we control for industry capacity utilization. Our method of estimating TFP assumes that industry capacity, especially capital, is fully utilized. This assumption is not satisfied in reality due to the adjustment costs of capital. During industry downturns, capital is underutilized and our method overestimates the amount of capital used as productive input. To circumvent this problem, we control for capacity utilization in our regressions.[15] Second, we control for age of

[14] In unreported regressions, we have examined whether our results are robust to using either early-stage or late-stage only VC investment, lagging the explanatory variables, to splitting the sample into VC-intensive industries (Computer and Communication Equipment) and others, and to splitting the sample into boom and bust period. We have obtained qualitatively very similar results.

[15] We obtain capacity utilization data from Federal Reserve Board of Governors (http://www.federalreserve.gov/releases/G17/). Our capacity utilization is the annual average of monthly capacity utilization which is computed as output index divided by capacity index.

capital.[16] Age of capital may affect TFP growth through either mismeasurement of capital and learning cost associated with introduction of new capital investments. When new equipment is introduced, its quality tends to be higher than that of old equipment. Nevertheless, the data may not be able to pick up this quality improvement and therefore may underestimate the amount of new equipment investment. As a consequence, we observe a faster TFP growth when new equipment investment is high and age of capital declines (Nelson, 1964). Arguments that support the opposite relation also exist. Investment in new equipment entails the costs of learning it and therefore TFP growth may slow down following investment in new equipment (Greenwood and Yorukoglu, 1997). Whelan (2007) argues that introduction of new equipment causes overestimation of new equipment investment, opposite to the Nelson's (1964) argument. When introduction of new equipment occurs, the relative price of new equipment against old equipment overstates the quality difference between old and new equipment. As a consequence, the new equipment investment may be overestimated. Third, we control for industry shipment. This specification incorporates the observation of a lower return to R&D seen in a larger firm (Adams and Jaffe, 1996).

Columns 5-12 in Table 6 presents the results controlling for the three aforementioned variables. Both privately-funded industrial R&D and the ratio of VC and privately-funded industrial R&D are instrumented. Similar to the results without the three control variables, the estimated coefficients on the ratio of VC are significant at the 5% level in none of these regressions. In summary, we therefore do not find a support for the positive impact of VC on TFP growth.[17]

[16] Capital age data are from http://www.bea.gov/bea/dn/FA2004/SelectTable.asp (Table 3.9ES. Current-Cost Average Age at Yearend of Private Fixed Assets by Industry (A)).

[17] In unreported regressions, we did the following robustness check. We lag the independent variables, smooth the data over 5 years, and exclude the drug industry which may need longer time of R&D to be realized into productivity growth. None of these modification changes the results qualitatively.

## 3.3 Labor Productivity Growth Results

We also run the same regressions as those for TFP growth, using labor productivity growth as the dependent variable. The results are reported in Table 7. Different from the results of TFP, the estimated coefficients on the ratio of VC and privately-funded R&D are positive for all and 5% significant for roughly a half of the instrumental variable regressions.

One may argue that labor productivity growth is a better measure of innovation than TFP growth, because the measurement of labor productivity does not require the measurement of non-labor input such as capital, material and energy. In particular, the measurement of capital and material is difficult due to quality heterogeneity and therefore the estimates of TFP heavily depends on the measurement method of capital and material. Nevertheless, labor productivity growth as a measure of innovation is also subject to important criticisms. Unlike TFP, labor productivity is only a partial measure of productivity. Even if there is no improvement in productive efficiency, labor productivity increases when other productive inputs are used more relative to labor input. In other words, for labor productivity to be a valid measure of technological progress, the proportion of each productive input needs to remain constant.

To examine whether this restriction is satisfied, we regress the growth of the other inputs relative to the growth of labor input. The results of this exercise are presented in Table 8. For every specification, the estimated coefficients on the ratio of VC and privately-funded R&D are positive, and they are significant when the dependent variable is either the relative growth of energy or non-energy material. In particular, for the latter case, 5% significance is obtained regardless of the choice of the definition of VC investment or the standard error formula. These results confirm our concern that the positive impact of VC investment on labor productivity just found is driven by substitutions of input factors away from labor. Interestingly, the results also show that privately-funded R&D is positively and significantly related with the technology substitution away from labor towards non-energy material.

Why do firms in VC-intensive industries tend to move towards less labor-intensive technology? One reason may have to do with a tougher corporate governance mechanism that venture capitalists usually bring in, as documented by Hochberg (2012). She finds that VC-backed firms adopt a better corporate governance structure than non VC-backed firms. Such strong governance presumably discourages incumbent management from setting up the entrenchment schemes including strong protection of own employees.[18] Another reason why firms in VC-intensive industries tend to move towards less labor-intensive technology may be to boost share prices. Financial analysts sometimes look at labor productivity at firm level to assess the firm's ability to generate cash flows in the future. Knowing this, new firms with a big financial appetite due to growth opportunities such as VC-backed firms may switch to less labor-intensive technology, increase labor-productivity, and drive the share price up. (Barley and Kunda, 2004, p.46) This explanation may also explain why privately-funded industrial R&D is positively related with the technology substitution away from labor. Not only VC-backed firms but also R&D intensive firms in general need long-term capital and therefore may have strong incentives to boost their stock prices. Finally, a data issue together with an increase in contract workers in VC-intensive industries may explain our findings. Employment and work hour figures collected in the Annual Survey of Manufacturers do not include outsourced labor. Outsourced labor is accounted as "purchased business service" that is a part of non-energy material input. Barley and Kunda (2004) document the shift to contracted work in Silicon Valley, and the cause and consequence of this shift. Silicon Valley receives the highest amount of VC investments every year, and therefore the accelerated substitution to non-energy material in the VC-intensive industry we find may be driven by the substitution from employed labor to outsourced

[18] Pagano and Volpin (2005) show that managers can entrench themselves by granting better protection to their employees. This is because such protection makes the firm less attractive to raiders as well as encourages the employees to fight against takeover bids.

labor. One reason why VC-backed firms may prefer outsourced labor relative to other firms is its flexibility. Without deep pocket or established products, it is important for new firms to be able to flexibly cut down the cost during the industry downturn. Contracted labor offers such flexibility that full-term employees may not be able to match (Barley and Kunda, 2004, p.46).

# 4 Why Does VC Investment Increase Patent Propensity?

Our results so far strongly suggest that VC investment increases patent counts but does not necessarily improve productive efficiency of U.S. manufacturing industries. In other words, VC investment appears to encourage the firms to patent their existing technology. Given that VC money is invested in new firms but not in established firms, there are a few reasons why VC money may increase the patent propensity of the industry.[19]

## 4.1 VC Investment May Increase Defensive Patents by Established Firms

First, VC-backing strengthens the competitiveness of new firms and this competitive pressure from these new firms may increase the patent propensity of established firms. These established firms may patent their inventions in order to block other firms from using them, even though patenting firms themselves never commercialize the patented inventions (Gilbert and Newbery, 1982). Supporting

[19] For the sample of Silicon Valley firms, Hellmann and Puri (2000) find that VC-backed firms are often start-ups (2 years old on average). There are several explanations why venture capitalists are specifically catered to start-up firms. First, a venture capitalist typically specializes in a narrow set of businesses and therefore may have an advantage in evaluating the businesses accurately. This accurate evaluation may lessen the cost associated with asymmetric information (Leland and Pyle, 1977; Chan, 1983). Second, VC may have a high flexibility in financial instruments because VC industries are relatively free from regulations. The financial instrument most commonly used by VC is convertible debts. Such equity instruments are not allowed for banks for instance. Cornelli and Yosha (2003) show how convertible debts can lessen the entrepreneur's incentive to engage in "window dressing" or short-termism. Third, not only financing portfolio firms, VC often supplies the firms with other resources essential to new firms. Those resources consist of legal and marketing expertise and are invaluable for new firms whose assets typically consist of their blueprints of prospective projects alone. New firms typically lack many types of resources that large firms internalize by taking advantage of their scale economy and business history. For instance, Lerner (1995) finds that VC-backed firms are more likely to make lawsuits related to trade secrecy infringement and suggests that venture capitalists actively help portfolio firms with these legal issues. Hellmann and Puri (2000) find that VC-backed firms can bring their products to the market faster than other non-VC-backed firms can, suggesting that venture capitalists can help new firms to find marketing channels and customers.

the importance of this blocking motive, Cohen, Nelson, and Walsh (2000) report that 82% of their respondents mention the blocking motive as one of their reasons to apply for patents and that this motive is second only to the motive of preventing copying (96%). The blocking motive is presumably stronger and established firms tend to patent more, when the threat of competition from start-ups becomes significant due to supports from venture capitalists.

We now attempt to test whether VC investment encourages established firms to patent for blocking motives. We hypothesize that patents with blocking motives are of lower quality than patents to be commercialized. With this hypothesis, it is anticipated that VC investment should cause the quality deterioration of patents held by established firms. Measuring the quality of patents is a challenging task, however, in particular due to our focus on the recent sample period that prohibits us from using the patent quality measures such as the number of citation that a patent received and the occurrence of patent renewal.[20] Therefore, we resort to the measures of patent quality which are all available at the time of patent application. The first measure is the number of citations that the patent makes. The second measure is the "number of claims" that specify in detail the "components" or building blocks of the patented invention. Lanjouw and Schankerman (2001) find that patents with higher number of claims are more likely to be litigated, indicating that these patents are more valuable. The third measure is "originality" that measures the technological breadth of the patents being cited. In particular, originality is computed as the Herfindahl index of cited patents, each of which is classified according to the U.S. patent class. Originality measure is related to the diversity of the knowledge on which the patent is based. The fourth measure is the average age of patents cited. The younger the age of patents cited, the more recent the knowledge on which the patent is based. Gonzalez (2006) reports that this recency of knowledge is positively related with the radicalness of memory chip inventions.

[20] Hall, Jaffe, and Trajtenberg (2005) find that the presence of highly cited patents is related to a higher Tobin's Q.

Hall, Jaffe, and Trajtenberg (2001) report that the raw number of these quality measures vary across industry and time due to change in institutional constraints. As a result, the comparison of these raw numbers over different time periods or industries are not likely to be meaningful. We therefore subset patent observations by U.S. patent class and application year, compute median values of each quality measures for each subset, and classify each patent as either above- or below-average quality against the U.S. patent class-application year median of the corresponding subset. For patent granted to established firms, we then compute the ratio of below-average quality patent against above-average quality patent. Here, we define established firms as patent holders that appear in 1989 Compustat. Therefore, if this ratio increases over time, it indicates the quality deterioration of patent held by established firms relative to those held by non-established firms, and *vice versa*.

We regress this ratio under the four different patent quality measures using the empirical model of KL. Our results are summarized in Table 9. Among all four measures, only the results using the originality measure are significant, and we therefore focus on these results. Note that the dependent variable is the ratio of patent with below-average originality in the established firms' patents. Therefore, the negative estimated coefficients on the ratio of VC and privately-funded R&D implies that the originality of patents held by the established firms improves relative to non-public firms when VC investment is high. This contradicts the blocking hypothesis that VC investment should be positively related to the quality deterioration of patents held by established firms.

### 4.2 VC Funding Favors New Firms That Have Higher Patent Propensity than Established Firms

Second, VC investments are geared towards start-up firms and these firms presumably have a higher patent propensity than established firms. Start-ups may use patents more often than established firms as a mean to appropriate returns to innovation. Levin et al. (1987) find that large firms generally rate patents as less effective mechanisms of appropriation than the other means such as secrecy, lead time, and sales or service efforts. Nevertheless, start-ups typically do not have any of these appropriation vehicles that established firms do because start-ups do not own their manufacturing and marketing capacities. Thus, these firms may use patents more often than established firms. Supporting this difference in patent propensity, Table 2 of Hall and Ziedonis (2001) report that design firms, specializing in product innovation in the US semiconductor industry have a higher propensity to patent than ones with manufacturing capacities. Using the survey of U.S. manufacturing firms, Table 7 of Cohen, Nelson, and Walsh (2000) also find that propensity to patent process innovations is negatively related with the presence of complementary sales and service assets, which new firms may not be able to afford.

### 4.3 Patent Propensity of New Firms Increases in Anticipation of VC Funding

Third, when financing becomes more available, new firms' patent propensity may increase because patents are an important means of obtaining funding. Hall and Ziedonis (2001) find that semiconductor firms often cite patents as a way to secure financing when the firms are young. Ueda (2004) also suggests that firms seeking for VC investment may have an increased incentive to patent their innovations, to lessen the VC's threat to expropriate their innovations.

## 5 Concluding Remarks

This paper asks the following questions. First, did VC investment continue to be a highly effective driver of patent activities during the explosive VC boom in late 1990s? Second, does VC money spur industrial innovation or patents? The answer to the first question is yes. By extending the sample period up until 2001, we reconfirm the results of KL. We find that VC investments are more effective than R&D in generating patents and its effect became stronger during the extended period. The answer to the second question is that VC money spurs patents but not necessarily industrial innovation. In particular, we find that VC investment is not significantly related with TFP growth; labor productivity is positively and significantly related with VC investment. Nevertheless, this positive relation is driven by the impact of VC investment on the substitution of energy and non-energy material against labor. This labor saving behavior in VC intensive industries may be driven by strong corporate governance by venture capitalists or by firms' desire to boost labor productivity and also stock prices. We also speculate that availability of VC may increases the patent propensity of new firms and\or the industry average patent propensity because VC stimulates new firm startups. Overall, our results suggest that the impact of VC investment is complex and a further examination is needed to understand what VC investment does for innovation.

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## Table 1: Summary Statistics

Notes: All figures are annual and computed from the panel of 19 manufacturing industries. The sample period is from 1967 to 2001. $ figures are all expressed in 2001 constant values.

| | TFP growth | Labor Productivity Growth | Number of Patent Applications | # of Firms receiving VC funding | Early-stage VC Investment (MM$) | Total VC Investment (MM$) | Total VC Investment/ Total R&D Expenditure | Company funded R&D (Mm$) | Federally funded R&D (MM$) |
|---|---|---|---|---|---|---|---|---|---|
| Minimum | -11.38% | -14.40% | 146 | 0 | 0 | 0 | 0.00% | 112 | 0 |
| Maximum | 28.29% | 40.53% | 14,337 | 471 | 2,606 | 9,530 | 73.50% | 29,419 | 28,871 |
| Mean | 1.30% | 3.64% | 2,615 | 27 | 55 | 167 | 2.74% | 3,947 | 1,605 |
| Median | 0.75% | 2.85% | 1,487 | 6 | 6 | 19 | 0.66% | 2,521 | 92 |
| SD | 4.18% | 5.99% | 3,108 | 58 | 162 | 580 | 6.21% | 4,106 | 4,149 |
| # Obs. | 646 | 646 | 646 | 646 | 646 | 646 | 646 | 646 | 646 |

## Table 2: Summary Statistics by Industry (Time Average)

Notes: All figures are average over respective annual data. The sample period is from 1967 to 2001. $ figures are 2001 constant values.

| | Industry | SIC Codes | TFP growth | Labor productivity growth | Number of Patent Applications | # of Firms receiving VC funding | Early-stage VC investment (MM$) | Total VC investment (MM$) | Company funded R&D (MM$) | Federally funded R&D (MM$) |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Food and kindred | 20 | 0.56% | 2.32% | 433 | 10 | 10 | 32 | 1,488 | 4 |
| 2 | Textile and apparel | 22,23 | 0.72% | 3.00% | 530 | 6 | 5 | 27 | 316 | 3 |
| 3 | Lumber and furniture | 24,25 | 0.11% | 1.51% | 799 | 3 | 4 | 13 | 299 | 0 |
| 4 | Paper | 26 | 0.48% | 2.26% | 575 | 2 | 3 | 10 | 1,248 | 2 |
| 5 | Industrial chemicals | 281,282,286 | 0.72% | 2.69% | 2,803 | 8 | 14 | 33 | 5,015 | 468 |
| 6 | Drugs | 283 | -0.23% | 2.58% | 1,650 | 43 | 142 | 393 | 6,617 | 31 |
| 7 | Other chemicals | 284-285, 287-289 | 0.23% | 2.28% | 2,048 | 4 | 5 | 15 | 2,028 | 70 |
| 8 | Petroleum refining and extraction | 13,29 | 0.52% | 2.21% | 295 | 8 | 22 | 68 | 2,516 | 115 |
| 9 | Rubber Products | 30 | 1.05% | 2.30% | 3,186 | 5 | 7 | 27 | 1,262 | 229 |
| 10 | Stone, clay and glass products | 32 | 0.69% | 1.75% | 739 | 5 | 9 | 18 | 828 | 36 |
| 11 | Primary metals | 33 | 0.55% | 2.00% | 586 | 3 | 7 | 21 | 1,058 | 129 |
| 12 | Fabricated metal products | 34 | 0.24% | 1.41% | 3,580 | 5 | 5 | 17 | 1,152 | 134 |
| 13 | Office and computing machines | 357 | 11.29% | 18.75% | 3,681 | 115 | 226 | 706 | 8,281 | 809 |
| 14 | Other non-electrical machinery | 351-356,358-359 | -0.09% | 1.56% | 11,278 | 23 | 30 | 79 | 4,058 | 112 |
| 15 | Communication and electronics | 366,367 | 5.50% | 9.65% | 4,558 | 121 | 305 | 976 | 11,235 | 4,318 |
| 16 | Other electrical equipment | 361-365,369 | 0.88% | 3.27% | 4,083 | 28 | 46 | 145 | 3,659 | 2,933 |
| 17 | Transportation equipment | 371,373-375,379 | 0.50% | 2.89% | 1,484 | 4 | 7 | 28 | 11,086 | 2,313 |
| 18 | Aircraft and missiles | 372,376 | 0.22% | 2.86% | 226 | 1 | 1 | 8 | 6,277 | 16,631 |
| 19 | Professional and scientific instruments | 38 | 0.72% | 3.81% | 7,151 | 115 | 200 | 558 | 6,571 | 2,167 |

## Table 3: Summary Statistics by Year

Notes: TFP growth and Labor Productivity Growth are equal weighted average over 19 manufacturing industries. Patent, # of Firms receiving VC funding and Total VC Investment are sum of industry-level figures. $ figures are 2001 constant values.

| Year | TFP growth | Labor Productivity Growth | Number of Patent Applications | # of Firms receiving VC funding | Total VC Investment (MM$) | Total VC Investment/ Total R&D Expenditure | Early VC Investment/ Total R&D Expenditure |
|---|---|---|---|---|---|---|---|
| 1968 | 1.67% | 4.51% | 42,436 | 25 | 58 | 0.07% | 0.05% |
| 1969 | 0.36% | 0.71% | 43,455 | 71 | 258 | 0.31% | 0.23% |
| 1970 | -1.69% | -0.88% | 42,949 | 67 | 159 | 0.20% | 0.12% |
| 1971 | 2.16% | 6.44% | 42,631 | 68 | 344 | 0.46% | 0.26% |
| 1972 | 2.89% | 5.95% | 39,713 | 59 | 278 | 0.36% | 0.23% |
| 1973 | 2.03% | 3.88% | 40,008 | 66 | 335 | 0.43% | 0.17% |
| 1974 | -0.62% | -0.66% | 39,113 | 45 | 125 | 0.17% | 0.08% |
| 1975 | -2.39% | -1.70% | 39,268 | 42 | 147 | 0.20% | 0.15% |
| 1976 | 2.79% | 5.88% | 38,689 | 44 | 108 | 0.14% | 0.07% |
| 1977 | 1.57% | 3.56% | 37,984 | 65 | 187 | 0.22% | 0.13% |
| 1978 | 1.16% | 1.94% | 36,851 | 125 | 356 | 0.41% | 0.21% |
| 1979 | 1.01% | 0.32% | 36,309 | 179 | 490 | 0.55% | 0.23% |
| 1980 | -0.71% | -0.97% | 36,294 | 254 | 900 | 0.99% | 0.51% |
| 1981 | 0.50% | 2.48% | 34,472 | 467 | 1,827 | 1.88% | 1.04% |
| 1982 | 0.04% | 0.59% | 34,287 | 578 | 2,263 | 2.20% | 0.89% |
| 1983 | 2.04% | 6.39% | 32,283 | 760 | 3,926 | 3.60% | 1.45% |
| 1984 | 1.62% | 5.50% | 33,990 | 844 | 3,922 | 3.31% | 1.37% |
| 1985 | 0.90% | 3.72% | 35,330 | 826 | 3,396 | 2.62% | 0.90% |
| 1986 | -0.03% | 4.27% | 36,389 | 809 | 3,619 | 2.69% | 1.07% |
| 1987 | 3.43% | 5.28% | 39,626 | 878 | 3,420 | 2.49% | 0.98% |
| 1988 | 0.94% | 3.64% | 43,872 | 799 | 3,231 | 2.33% | 1.00% |
| 1989 | -0.69% | 0.81% | 46,897 | 758 | 2,952 | 2.12% | 0.93% |
| 1990 | -0.40% | 1.91% | 49,727 | 649 | 2,397 | 1.70% | 0.65% |
| 1991 | -0.68% | 2.32% | 50,411 | 529 | 1,630 | 1.12% | 0.36% |
| 1992 | 2.72% | 5.06% | 53,586 | 571 | 2,668 | 1.60% | 0.42% |
| 1993 | 0.99% | 4.41% | 56,566 | 471 | 2,041 | 1.56% | 0.58% |
| 1994 | 2.83% | 6.07% | 63,527 | 451 | 2,075 | 1.42% | 0.53% |
| 1995 | 2.33% | 4.39% | 76,360 | 603 | 3,198 | 1.84% | 0.81% |
| 1996 | 1.58% | 5.51% | 72,481 | 736 | 3,897 | 1.88% | 0.67% |
| 1997 | 1.95% | 4.15% | 85,448 | 902 | 5,478 | 4.10% | 1.52% |
| 1998 | 0.40% | 3.26% | 84,124 | 1,144 | 6,385 | 4.80% | 1.81% |
| 1999 | 2.73% | 6.05% | 86,638 | 983 | 10,853 | 8.31% | 1.82% |
| 2000 | 1.82% | 3.86% | 84,483 | 1,384 | 22,666 | 16.92% | 4.06% |
| 2001 | -1.01% | -0.36% | 73,072 | 1,081 | 12,312 | 9.33% | 2.36% |

# Table 4: Correlation Table

Notes: Both TFP Growth and NBER TFP Growth are computed as output growth minus the weighted sum of the five production factors (non-production employment, production work hour, capital, energy, and non-energy material). For the computation of TFP Growth, we include benefits such as pension contribution to obtain the weights for each factor growth. Benefits are not included when computing the weights for NBER TFP Growth. Labor Productivity Growth is output growth minus growth of total employment. Production Labor Productivity Growth is output growth minus growth of production work hours. P-values for the null of no correlation are presented in parentheses.

| | TFP growth | NBER TFP growth | Labor Productivity Growth | Production Labor Productivity Growth | Patent | Early-stage VC Investment (MM$) | Total VC Investment (MM$) | Federally funded R&D (MM$) | Company funded R&D (Mm$) |
|---|---|---|---|---|---|---|---|---|---|
| TFP Growth | 1 | | | | | | | | |
| NBER TFP Growth | 0.9073 | 1 | | | | | | | |
| | (0.0000) | | | | | | | | |
| Labor Productivity Growth | 0.8583 | 0.7829 | 1 | | | | | | |
| | (0.0000) | (0.0000) | | | | | | | |
| Production Labor Productivity Growth | 0.8040 | 0.7274 | 0.8989 | 1 | | | | | |
| | (0.0000) | (0.0000) | (0.0000) | | | | | | |
| Patent | 0.1242 | 0.0981 | 0.1511 | 0.1850 | 1 | | | | |
| | (0.0016) | (0.0127) | (0.0001) | (0.0000) | | | | | |
| Early-Stage VC Investment | 0.2990 | 0.2566 | 0.3520 | 0.4129 | 0.3994 | 1 | | | |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | | | | |
| Total VC Investment | 0.2863 | 0.2407 | 0.3208 | 0.3869 | 0.3841 | 0.9655 | 1 | | |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | | | |
| Federally funded R&D | -0.0199 | -0.0248 | 0.0196 | 0.0473 | -0.0785 | 0.0135 | 0.0125 | 1 | |
| | (0.6137) | (0.5285) | (0.6196) | (0.2298) | (0.0461) | (0.7311) | (0.7517) | | |
| Company funded R&D | 0.2444 | 0.2075 | 0.3398 | 0.3813 | 0.3385 | 0.6020 | 0.5504 | 0.3011 | 1 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | |
| Total R&D | 0.1908 | 0.1649 | 0.1839 | 0.2734 | 0.2456 | 0.5229 | 0.5606 | -0.0943 | 0.1416 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0165) | (0.0003) |

## Table 5: Patent Production Function
## Replication of Table 4 in Kortum and Lerner (2000)

Notes: In Panel A, the coefficients on privately funded industrial R&Ds are fixed to 0.2 and 0.5, and the instrument for the ratio of VC to privately funded R&D is the interaction of ERISA dummy variable with average of venture funding relative to corporate R&D between 1968 and 1975. In Panel B, the instrument for privately funded industrial R&D is gross industry product and the instrument for the ratio of VC to privately funded R&D is the interaction of ERISA dummy variable with average of venture funding relative to corporate R&D.

For the first two columns of each panel, the average is computed over the period from 1968 to 1978, and for the second two columns, the average is computed over the period from 1968 to 1975. Year and industry dummy variables are included in all regressions. Figures in parentheses and brackets are standard errors based on the Newey-West autocorrelation-consistent covariance estimator (with a maximum of three lags) and those on the two-way cluster-robust covariance estimator across industry and time, respectively. Standard errors for the parameter *b* are calculated using the delta method. The 10%, 5%, and 1% levels of significance are indicated by *, **, and ***, respectively. In all regressions, we present two measures of the goodness of fit: the overall $R^2$ and $R^2$ when compared against a regression with year and industry dummy variables only, where the latter is computed as (Dummy_only SSR - SSR) / Dummy_only SSR, and SSR refers to the sum of squared residuals of the various regressions.

**Panel A: IV is ERISA*Prior Funding.**

| Sample Period | 1968-01 | 1968-92 | 1968-01 | 1968-92 | 1968-01 | 1968-92 | 1968-01 | 1968-92 |
|---|---|---|---|---|---|---|---|---|
| Privately funded industrial R&D ($\alpha$) | 0.20 | 0.20 | 0.20 | 0.20 | 0.50 | 0.50 | 0.50 | 0.50 |
| | ( - ) | ( - ) | ( - ) | ( - ) | ( - ) | ( - ) | ( - ) | ( - ) |
| | [ - ] | [ - ] | [ - ] | [ - ] | [ - ] | [ - ] | [ - ] | [ - ] |
| VC/privately funded R&D ($\alpha * b$): | | | | | | | | |
| Firms receiving funding | 26.56 | 14.90 | | | 21.93 | 10.25 | | |
| | (8.92)*** | (6.09)** | | | (8.39)*** | (5.64)* | | |
| | [13.22]** | [6.62]** | | | [11.21]* | [7.29] | | |
| Venture disbursements | | | 5.63 | 3.69 | | | 4.77 | 2.10 |
| | | | (1.66)*** | (1.56)** | | | (1.61)*** | (1.22)* |
| | | | [1.87]*** | [0.96]*** | | | [1.62]*** | [0.95]** |
| Federally funded industrial R&D | -0.00 | -0.01 | 0.02 | -0.00 | -0.01 | -0.01 | 0.01 | -0.01 |
| | (0.01) | (0.00) | (0.01) | (0.00) | (0.01) | (0.01) | (0.01) | (0.01) |
| | [0.01] | [0.01] | [0.02] | [0.01] | [0.01] | [0.01] | [0.01] | [0.01] |
| $R^2$ | 0.96 | 0.99 | 0.97 | 0.99 | 0.96 | 0.98 | 0.96 | 0.98 |
| $R^2$ relative to dummy variable only case | 0.06 | 0.04 | 0.14 | 0.09 | 0.05 | 0.02 | 0.10 | 0.03 |
| Number of observations | 646 | 475 | 646 | 475 | 646 | 475 | 646 | 475 |
| Implied potency of venture funding (*b*) | 132.78 | 74.50 | 28.17 | 18.45 | 43.87 | 20.50 | 9.55 | 4.21 |
| | (44.61)*** | (30.43)** | (8.28)*** | (7.81)** | (16.79)*** | (11.27)* | (3.21)*** | (2.43)* |
| | [66.12]** | [33.12]** | [9.37]*** | [4.79]*** | [22.42]* | [14.59] | [3.23]*** | [1.89]** |

**Panel B: IVs are ERISA*Prior Funding and Gross Industry Product.**

| Sample Period | 1968-01 | 1968-92 | 1968-01 | 1968-92 | 1968-01 | 1968-92 | 1968-01 | 1968-92 |
|---|---|---|---|---|---|---|---|---|
| Privately funded industrial R&D ($\alpha$) | 0.51 | 0.30 | 0.48 | 0.28 | 0.51 | 0.31 | 0.48 | 0.29 |
| | (0.09)*** | (0.07)*** | (0.09)*** | (0.09)*** | (0.09)*** | (0.07)*** | (0.10)*** | (0.09)*** |
| | [0.16]*** | [0.11]*** | [0.13]*** | [0.12]** | [0.16]*** | [0.11]*** | [0.13]*** | [0.12]** |
| VC/privately funded R&D ($\alpha * b$): | | | | | | | | |
| Firms receiving funding | 21.77 | 13.28 | | | 22.58 | 12.08 | | |
| | (8.30)*** | (6.17)** | | | (8.75)*** | (5.91)** | | |
| | [11.71]* | [6.81]* | | | [12.47]* | [7.46] | | |
| Venture disbursements | | | 4.83 | 3.25 | | | 5.09 | 2.75 |
| | | | (1.61)*** | (1.71)* | | | (1.90)*** | (1.74) |
| | | | [1.75]*** | [1.16]*** | | | [1.88]*** | [1.64]* |
| Federally funded industrial R&D | -0.01 | -0.01 | 0.01 | -0.01 | -0.01 | -0.01 | 0.01 | -0.01 |
| | (0.01) | (0.00) | (0.01) | (0.00) | (0.01) | (0.00) | (0.01) | (0.00) |
| | [0.01] | [0.01] | [0.01] | [0.01] | [0.01] | [0.01] | [0.01] | [0.01] |
| $R^2$ | 0.97 | 0.99 | 0.97 | 0.99 | 0.97 | 0.99 | 0.97 | 0.99 |
| $R^2$ relative to dummy variable only case | 0.18 | 0.16 | 0.24 | 0.22 | 0.18 | 0.16 | 0.22 | 0.19 |
| Number of observations | 646 | 475 | 646 | 475 | 646 | 475 | 646 | 475 |
| Implied potency of venture funding (*b*) | 42.64 | 43.67 | 10.07 | 11.48 | 44.13 | 39.19 | 10.60 | 9.36 |
| | (17.87)** | (27.01) | (4.02)** | (8.95) | (18.58)** | (24.82) | (4.58)** | (7.89) |
| | [29.99] | [32.16] | [5.32]* | [8.31] | [31.50] | [32.81] | [5.66]* | [8.63] |

# Table 6: Total Factor Productivity Growth

Notes: The instrument for privately funded industrial R&D is gross industry product and the instrument for the ratio of VC to privately funded R&D is the interaction of ERISA dummy variable with average of venture funding relative to corporate R&D over the period of 1968-1978. Capacity utilization is the annual average of monthly capacity utilization which is computed as output index divided by capacity index. Figures in parentheses and brackets are standard errors based on the Newey-West autocorrelation-consistent covariance estimator (with a maximum of three lags) and those on the two-way cluster-robust covariance estimator across industry and time, respectively. Standard errors for the parameter *b* are calculated using the delta method. The 10%, 5%, and 1% levels of significance are indicated by *, **, and ***, respectively. In all regressions, we present two measures of the goodness of fit: the overall $R^2$ and $R^2$ when compared against a regression with year and industry dummy variables only, where the latter is computed as (Dummy_only SSR - SSR) / Dummy_only SSR, and SSR refers to the sum of squared residuals of the various regressions. The sample period is from 1968 to 2001.

| | OLS | | Instrumental Variable Regressions | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Privately funded industrial R&D (α) | -0.64 | -0.59 | 2.16 | 2.04 | 1.05 | 1.08 | 3.42 | 2.94 | 1.27 | 2.22 | 0.73 | 0.41 |
| | (0.52) | (0.54) | (1.33) | (1.23)* | (1.37) | (1.42) | (1.60)** | (1.67)* | (1.83) | (2.24) | (2.02) | (2.23) |
| | [0.60] | [0.62] | [2.21] | [1.93] | [2.26] | [2.35] | [2.47] | [2.31] | [2.61] | [2.69] | [2.92] | [3.06] |
| VC/privately funded R&D ($\alpha * b$): | | | | | | | | | | | | |
| Firms receiving funding | 26.74 | | 82.74 | | -30.35 | | 62.46 | | 86.37 | | -62.37 | |
| | (29.04) | | (88.51) | | (81.46) | | (94.62) | | (86.60) | | (81.47) | |
| | [34.49] | | [80.04] | | [78.79] | | [94.46] | | [77.33] | | [70.56] | |
| Venture disbursements | | 3.99 | | 20.11 | | -6.14 | | 18.01 | | 19.90 | | -9.38 |
| | | (3.18) | | (20.45) | | (16.48) | | (21.73) | | (19.19) | | (16.38) |
| | | [2.34]* | | [11.28]* | | [11.32] | | [12.99] | | [10.98]* | | [9.23] |
| Federally funded industrial R&D | -0.00 | 0.01 | -0.05 | 0.02 | -0.02 | -0.04 | -0.12 | -0.03 | -0.02 | 0.02 | -0.03 | -0.05 |
| | (0.05) | (0.05) | (0.06) | (0.10) | (0.06) | (0.09) | (0.08) | (0.13) | (0.07) | (0.08) | (0.08) | (0.09) |
| | [0.06] | [0.06] | [0.08] | [0.08] | [0.08] | [0.11] | [0.11] | [0.12] | [0.09] | [0.11] | [0.11] | [0.12] |
| Capacity Utilization | | | | | 0.12 | 0.13 | | | | | 0.10 | 0.10 |
| | | | | | (0.04)*** | (0.04)*** | | | | | (0.04)** | (0.04)** |
| | | | | | [0.04]*** | [0.04]*** | | | | | [0.04]** | [0.04]** |
| Age of Capital | | | | | | | 0.79 | 0.55 | | | 0.70 | 0.79 |
| | | | | | | | (0.35)** | (0.50) | | | (0.50) | (0.50) |
| | | | | | | | [0.50] | [0.45] | | | [0.34]** | [0.43]* |
| Shipment | | | | | | | | | 6.56 | -1.35 | 11.46 | 15.60 |
| | | | | | | | | | (7.75) | (11.35) | (11.35) | (11.35) |
| | | | | | | | | | [9.38] | [9.61] | [8.13] | [12.02] |
| $R^2$ | 0.51 | 0.51 | 0.51 | 0.52 | 0.57 | 0.57 | 0.52 | 0.53 | 0.52 | 0.52 | 0.58 | 0.58 |
| $R^2$ relative to dummy variable only case | 0.01 | 0.01 | 0.02 | 0.02 | 0.13 | 0.13 | 0.03 | 0.04 | 0.02 | 0.03 | 0.15 | 0.15 |
| Number of observations | 646 | 646 | 646 | 646 | 614 | 614 | 646 | 646 | 646 | 646 | 614 | 614 |
| Implied potency of venture funding (*b*) | -41.67 | -6.78 | 38.39 | 9.86 | -28.92 | -5.71 | 18.26 | 6.13 | 68.24 | 8.95 | -85.67 | -23.16 |
| | (65.30) | (10.12) | (44.10) | (11.11) | (92.19) | (18.10) | (29.33) | (9.19) | (110.31) | (8.61) | (264.33) | (147.11) |
| | [76.82] | [10.69] | [49.79] | [10.79] | [105.42] | [18.36] | [30.66] | [7.19] | [151.78] | [11.73] | [342.79] | [180.30] |

# Table 7: Labor Productivity Growth

Notes: The instrument for privately funded industrial R&D is gross industry product and the instrument for the ratio of VC to privately funded R&D is the interaction of ERISA dummy variable with average of venture funding relative to corporate R&D over the period of 1968-1978. Capacity utilization is the annual average of monthly capacity utilization which is computed as output index divided by capacity index. Figures in parentheses and brackets are standard errors based on the Newey-West autocorrelation-consistent covariance estimator (with a maximum of three lags) and those on the two-way cluster-robust covariance estimator across industry and time, respectively. Standard errors for the parameter $b$ are calculated using the delta method. The 10%, 5%, and 1% levels of significance are indicated by *, **, and ***, respectively. In all regressions, we present two measures of the goodness of fit: the overall $R^2$ and $R^2$ when compared against a regression with year and industry dummy variables only, where the latter is computed as (Dummy_only SSR - SSR) / Dummy_only SSR, and SSR refers to the sum of squared residuals of the various regressions. The sample period is from 1968 to 2001.

| | **OLS** | | **Instrumental Variable Regressions** | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Privately funded industrial R&D ($\alpha$) | 0.17 | 0.16 | 3.37 | 3.02 | 1.74 | 1.62 | 4.47 | 2.99 | 2.59 | 4.98 | 1.32 | 2.19 |
| | (0.71) | (0.74) | (1.78)* | (1.65)* | (1.81) | (1.68) | (2.20)** | (2.47) | (2.50) | (3.20) | (2.61) | (2.85) |
| | [0.87] | [0.85] | [3.03] | [2.26] | [3.10] | [2.70] | [3.63] | [3.06] | [3.85] | [4.48] | [3.99] | [4.06] |
| VC/privately funded R&D ($\alpha * b$): | | | | | | | | | | | | |
| Firms receiving funding | 41.76 | | 248.21 | | 123.35 | | 230.67 | | 251.42 | | 105.42 | |
| | (40.52) | | (119.61)** | | (100.10) | | (124.42)* | | (118.35)** | | (103.96) | |
| | [49.86] | | [143.13]* | | [112.16] | | [152.54] | | [140.61]* | | [112.90] | |
| Venture disbursements | | 3.59 | | 54.09 | | 22.75 | | 54.16 | | 51.90 | | 21.87 |
| | | (4.82) | | (26.38)** | | (16.14) | | (28.65)* | | (24.45)** | | (17.52) |
| | | [3.93] | | [22.17]** | | [10.75]** | | [22.57]** | | [20.86]** | | [11.67]* |
| Federally funded industrial R&D | 0.06 | 0.07 | 0.02 | 0.22 | 0.07 | 0.15 | -0.04 | 0.22 | 0.04 | 0.15 | 0.07 | 0.13 |
| | (0.07) | (0.06) | (0.08) | (0.16) | (0.08) | (0.11) | (0.09) | (0.19) | (0.08) | (0.12) | (0.08) | (0.10) |
| | [0.07] | [0.07] | [0.10] | [0.19] | [0.09] | [0.11] | [0.15] | [0.23] | [0.10] | [0.18] | [0.12] | [0.16] |
| Capacity Utilization | | | | | 0.19 | 0.18 | | | | | 0.18 | 0.19 |
| | | | | | (0.05)*** | (0.05)*** | | | | | (0.05)*** | (0.05)*** |
| | | | | | [0.06]*** | [0.06]*** | | | | | [0.06]*** | [0.06]*** |
| Age of Capital | | | | | | | 0.69 | -0.02 | | | 0.39 | 0.16 |
| | | | | | | | (0.45) | (0.78) | | | (0.78) | (0.78) |
| | | | | | | | [0.72] | [0.61] | | | [0.46] | [0.59] |
| Shipment | | | | | | | | | 5.80 | -14.41 | 8.25 | -2.14 |
| | | | | | | | | | (12.07) | (17.62) | (17.62) | (17.62) |
| | | | | | | | | | [17.37] | [23.52] | [11.46] | [14.47] |
| $R^2$ | 0.59 | 0.59 | 0.61 | 0.62 | 0.66 | 0.66 | 0.61 | 0.62 | 0.61 | 0.62 | 0.66 | 0.66 |
| $R^2$ relative to dummy variable only case | 0.00 | 0.00 | 0.04 | 0.06 | 0.18 | 0.18 | 0.04 | 0.07 | 0.04 | 0.06 | 0.18 | 0.19 |
| Number of observations | 646 | 646 | 646 | 646 | 614 | 614 | 646 | 646 | 646 | 646 | 614 | 614 |
| Implied potency of venture funding ($b$) | 245.96 | 21.93 | 73.61 | 17.90 | 70.93 | 14.01 | 51.64 | 18.13 | 97.20 | 10.41 | 79.79 | 10.00 |
| | (960.72) | (88.62) | (50.99) | (13.53) | (90.95) | (17.18) | (39.39) | (21.25) | (102.44) | (7.48) | (183.70) | (14.85) |
| | [1,134.21] | [101.34] | [74.07] | [15.65] | [128.10] | [22.25] | [54.01] | [21.28] | [150.78] | [9.89] | [268.04] | [20.39] |

# Table 8: Factor Substitutions

Notes: The instrument for privately funded industrial R&D is gross industry product and the instrument for the ratio of VC to privately funded R&D is the interaction of ERISA dummy variable with average of venture funding relative to corporate R&D over the period of 1968-1978. Figures in parentheses and brackets are standard errors based on the Newey-West autocorrelation-consistent covariance estimator (with a maximum of three lags) and those on the two-way cluster-robust covariance estimator across industry and time, respectively. Standard errors for the parameter *b* are calculated using the delta method. The 10%, 5%, and 1% levels of significance are indicated by *, **, and ***, respectively. In all regressions, we present two measures of the goodness of fit: the overall $R^2$ and $R^2$ when compared against a regression with year and industry dummy variables only, where the latter is computed as (Dummy_only SSR - SSR) / Dummy_only SSR, and SSR refers to the sum of squared residuals of the various regressions. The sample period is from 1968 to 2001.

| | Dependent variable is the growth of | | | | | |
|---|---|---|---|---|---|---|
| | **Energy/Employment** | | **Capital/Employment** | | **Non-Energy Material/ Employment** | |
| Privately funded industrial R&D ($\alpha$) | 0.52 | 0.13 | -1.26 | -1.35 | 4.63 | 4.17 |
| | (1.45) | (1.81) | (1.24) | (1.21) | (1.43)*** | (1.39)*** |
| | [1.77] | [2.22] | [1.62] | [1.37] | [1.32]*** | [1.04]*** |
| VC/privately funded R&D ($\alpha * b$): | | | | | | |
| Firms receiving funding | 268.45 | | 63.46 | | 317.47 | |
| | (109.92)** | | (105.76) | | (120.00)*** | |
| | [152.34]* | | [43.76] | | [129.76]** | |
| Venture disbursements | | 36.18 | | 18.91 | | 48.29 |
| | | (19.51)* | | (18.07) | | (21.81)** |
| | | [24.46] | | [4.17]*** | | [20.38]** |
| Federally funded industrial R&D | 0.12 | 0.24 | 0.08 | 0.15 | -0.13 | 0.04 |
| | (0.15) | (0.17) | (0.08) | (0.13) | (0.18) | (0.18) |
| | [0.15] | [0.22] | [0.09] | [0.14] | [0.22] | [0.21] |
| $R^2$ | 0.71 | 0.71 | 0.69 | 0.69 | 0.37 | 0.37 |
| $R^2$ relative to dummy variable only case | 0.01 | 0.01 | 0.00 | 0.00 | 0.02 | 0.03 |
| Number of observations | 646 | 646 | 646 | 646 | 646 | 646 |
| Implied potency of venture funding (*b*) | 519.65 | 274.45 | -50.38 | -14.03 | 68.59 | 11.57 |
| | (1,461.99) | (3,790.32) | (102.42) | (18.48) | (33.73)** | (7.12) |
| | [1,699.73] | [4,580.66] | [104.64] | [20.57] | [24.14]*** | [3.94]*** |

# Table 9: Patenting by 1989 Compustat Firms

Notes: The instrument for privately funded industrial R&D is gross industry product and the instrument for the ratio of VC to privately funded R&D is the interaction of ERISA dummy variable with average of venture funding relative to corporate R&D over the period of 1968-1978. Figures in parentheses and brackets are standard errors based on the Newey-West autocorrelation-consistent covariance estimator (with a maximum of three lags) and those on the two-way cluster-robust covariance estimator across industry and time, respectively. Standard errors for the parameter *b* are calculated using the delta method. The 10%, 5%, and 1% levels of significance are indicated by *, **, and ***, respectively. In all regressions, we present two measures of the goodness of fit: the overall $R^2$ and $R^2$ when compared against a regression with year and industry dummy variables only, where the latter is computed as (Dummy_only SSR - SSR) / Dummy_only SSR, and SSR refers to the sum of squared residuals of the various regressions. The sample period is from 1976 to 2001.

| | Dependent variable is the fraction of patents held by 1989 Compustat Firms | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | that make **below-average citations**. | | that make **below-average claims**. | | with **below-average originality**. | | whose cited patents are **above-average age**. | |
| Privately funded industrial R&D ($\alpha$) | 0.01 | 0.01 | 0.01 | 0.00 | 0.10 | 0.13 | 0.03 | 0.02 |
| | (0.03) | (0.03) | (0.03) | (0.03) | (0.06)* | (0.06)** | (0.04) | (0.04) |
| | [0.05] | [0.04] | [0.05] | [0.04] | [0.09] | [0.08] | [0.04] | [0.06] |
| VC/privately funded R&D ($\alpha * b$): | | | | | | | | |
| Firms receiving funding | 0.36 | | 1.15 | | -11.15 | | 3.14 | |
| | (3.46) | | (3.71) | | (5.42)** | | (4.31) | |
| | [3.15] | | [4.06] | | [5.43]** | | [4.61] | |
| Venture disbursements | | 0.54 | | 0.37 | | -1.36 | | -0.05 |
| | | (0.48) | | (0.42) | | (0.73)* | | (0.49) |
| | | [0.44] | | [0.49] | | [0.69]** | | [0.54] |
| Federally funded industrial R&D | 0.00 | 0.00 | -0.00 | 0.00 | -0.01 | -0.02 | 0.00 | 0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.01)* | (0.01)** | (0.00)* | (0.00) |
| | [0.00] | [0.00] | [0.00] | [0.01] | [0.01] | [0.01] | [0.00] | [0.00] |
| $R^2$ | 0.60 | 0.61 | 0.54 | 0.54 | 0.52 | 0.52 | 0.47 | 0.47 |
| $R^2$ relative to dummy variable only case | 0.00 | 0.01 | 0.00 | 0.00 | 0.05 | 0.05 | 0.02 | 0.01 |
| Number of observations | 494 | 494 | 494 | 494 | 494 | 494 | 494 | 494 |
| Implied potency of venture funding ($b$) | 46.43 | 72.92 | 202.74 | 115.66 | -110.16 | -10.71 | 100.52 | -2.31 |
| | (453.83) | (306.56) | (1,213.82) | (1,090.18) | (82.41) | (6.04)* | (194.15) | (19.61) |
| | [519.88] | [422.34] | [1,777.45] | [1,532.80] | [98.75] | [6.10]* | [258.60] | [17.99] |