Venture Capital and Innovation: Which is First?*

Masayuki Hirukawa[†]
Northern Illinois University

Masako Ueda[‡]
University of Wisconsin - Madison

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Abstract

Policy makers typically interpret positive relations between venture capital investments and innovations as an evidence that venture capital investments stimulate innovation (*"VC-first hypothesis"*). This interpretation is, however, one-sided because there may be a reverse causality that innovations induce venture capital investments (*"innovation-first hypothesis"*): an arrival of new technology increases demands for venture capital by driving new firm startups. We analyze this causality issue of venture capital investments and innovation in the US manufacturing industry using both total factor productivity (TFP) growth and patent counts as measures of innovation. Using a panel AR regression as well as industry-by-industry AR regressions, we find that TFP growth is often positively and significantly related with future VC investment, which is consistent with the innovation-first hypothesis. We find little evidence that supports the VC-first hypothesis. More surprisingly, one-year lagged VC investments are often negatively and significantly related with both TFP growth and patent counts.

Keywords: Venture Capital, Innovation, Granger-Causality

JEL Classifications: G24, D24, O31, O32.

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[†]Department of Economics, E-mail: mhirukawa@niu.edu.

[‡]School of Business, E-mail: mueda@bus.wisc.edu.

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Abstract

Policy makers typically interpret positive relations between venture capital investments and innovations as an evidence that venture capital investments stimulate innovation (*"VC-first hypothesis"*). This interpretation is, however, one-sided because there may be a reverse causality that innovations induce venture capital investments (*"innovation-first hypothesis"*): an arrival of new technology increases demands for venture capital by driving new firm startups. We analyze this causality issue of venture capital investments and innovation in the US manufacturing industry using both total factor productivity (TFP) growth and patent counts as measures of innovation. Using a panel AR regression as well as industry-by-industry AR regressions, we find that TFP growth is often positively and significantly related with future VC investment, which is consistent with the innovation-first hypothesis. We find little evidence that supports the VC-first hypothesis. More surprisingly, one-year lagged VC investments are often negatively and significantly related with both TFP growth and patent counts.

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1 Introduction

Policy makers who aim to stimulate economic growth often attempt to create or expand their local venture capital industries. These attempts include Yozma program in Israel, Small Business Investment Company ("SBIC") program in the United States, and various initiatives to create stock markets where listing requirements are less stringent than traditional markets.[1] There are two common rationales for this attempt; one is that venture capitalists mitigate a problem of underinvestment in innovative activities by small and new firms (Hall, 2002) and the other is that venture capitalists can help new firms to grow fast and become profitable (Sahlman, 1990). Thus, creating infrastructure for and subsidizing venture capitalists are supposed to make more financial and managerial resources available for those firms than otherwise and thereby encourage innovations (see, for instance, European Commission, 1995, for Europe and Venture Enterprise Center, 1991, for Japan).

There are indeed both ad hoc and academic evidence suggesting that firms grow fast and overcome the problem of underinvestment in innovative activities if they are backed by venture capitalists. At firm level, Hellmann and Puri (2000) and Engel (2002) find that venture capital backed firms grow faster than their industry counterparts. Rapid growth also characterizes venture-backed firms in Japan (Suzuki, 1996). Regarding innovation, Kortum and Lerner (2001) find that patents granted to venture capital backed companies are cited more often than other patents suggesting that venture capital backed companies are engaged in important innovative activities. At industry level, Kortum and Lerner find that in the U.S. venture capital investments account for patent count disproportionately relative to R&D expenditures. Using German data, Tykova (2000)

[1] Black and Gilson (1998) argue that stock markets facilitate exits of venture capitalist supporting creation of stock market segments for young firms.

also finds the positive relation between venture capital investment and patent application.[2]

A common interpretation of the results found in the literature cited above is that venture capital ("VC") spurs growth and innovation of new firms. Hereafter, we call this view the *VC-first* hypothesis. This interpretation is one-sided however, because there may be an opposite causality; when there arise abundant opportunities for new firms to innovate and/or to grow fast, these firms demand venture capital investments and as a consequence venture capital markets grow because venture capitalists are complementary assets for such firms.[3] Such opportunities frequently arise when significant innovations arrive. There are two reasons for this. First, an arrival of a substantial innovation may create business opportunities and trigger firm startups. For instance, a drastic cost reduction in computer technology enlarged the scope of computer users, not only professional users but also individual customers. Due to this expansion of the market, a number of new computer manufacturers such as Apple, and Dell, emerged and entered the market that used to be dominated by IBM. Second, there are numerous literatures from industrial organization which argues that entrant firms are more likely to innovate than established firms when the scale of potential innovation is large. Thus, arrival of significant innovation is supposed to be positively associated

[2] There are other evidences that support the role of venture-backed firms in driving innovations and growth. According to NVCA (1998), 80% of venture capital investment is towards high-tech industries such as computers, communications, medical and health, and biotechnology.

[3] The complementarity between new firms and venture capital may arise from various sources. 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, venture capital may have a high flexibility in financial instruments because venture capital industries are relatively free from regulations. The financial instrument most commonly used by venture capital is convertible debts. Such equity instruments are not allowed for banks for instance. Cornelli and Yosha (1997) show how convertible debts can lessen the entrepreneur's incentive to engage in "window dressing" or short-termism. Third, not only financing portfolio firms, venture capital 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 (1994) finds that venture-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 venture-backed firms can bring their products to the market faster than other non-venture-backed firms can suggesting venture capitalists can help new firms to find marketing channels and customers.

with new firm entries. (Gans and Stern, 2000, Gilbert and Newbery, 1982, and Reinganum, 1983) Therefore, the venture capital market may grow because innovation spurs new firm start-up. On contrast to the VC-first hypothesis, we call this view *innovation-first* hypothesis.

This paper addresses the causality issues described above by studying dynamic panel data of U.S. manufacturing industries. We study two types of VC investment measures (the first and the follow-on investment) and two types of innovation measures (TFP growth and patent counts). Using a panel AR regression, we begin with testing for Granger type causality between innovation and VC investments. We also run AR regressions for each of the five VC-intensive industries.

We find weak evidence for the VC-first hypothesis when TFP growth is used as the measure of innovation. In particular, in the panel AR regressions under various specifications, two-year lagged first round VC investment is positively and significantly related with TFP growth. Nevertheless, lagged follow-on round VC investment is not significantly related with TFP growth. We do not find any evidence for the VC-first hypothesis when patent is used as the measure of innovation.

Surprisingly, we find that one-year lagged VC investment is often significantly and *negatively* related with both TFP growth and patent counts. The negative relation between lagged VC investment and TFP growth is consistent with the bubbles and crashes theory (e.g. Abreu and Brunnermeier, 2003). This theory contends that economic booms will trigger subsequent crashes. As VC investments increase during economic booms and TFP growth slows down during crashes due to low capacity utilization, the bubbles and crashes theory predicts that VC investment boom leads slow-down in TFP growth. The negative relation between lagged VC investment and patent counts is consistent with the firm-level evidence by Engel and Keilbach (2007) and Caselli, Gatti and Perrini (2008). These two papers find that firms characterized by high patenting experience low patenting activity but high sales growth after VC financing in German data and Italian data, respectively. One explanation behind these findings is that venture capitalists change the strategy of their portfolio firms from innovating to cashing out from innovations.

We find some evidence for the innovation-first hypothesis when TFP growth is used as the measure of innovation. In particular, in the panel AR regressions and the AR regression of Communication and Electronic industries, we find that lagged TFP growth is positively related with the first round VC investment. We do not find any evidence for the innovation-first hypothesis when patent counts are used as the measure of innovation.

Besides the articles cited above, this paper is closely related to literatures on financial development and growth. For instance, close to the spirit of this paper, Robinson (1952) argues how financial development follows economic development. Greenwood and Jovanovic (1999) rigorously model how economic growth and financial development are mutually dependent. Recently, Levine, Loayza, and Beck (2000) find that exogenous development of financial intermediary sectors enhances economic growth. Compared to the literature that studies banking sectors and stock markets, there exist few academic studies on the economic impact of VC. One important exception is 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 size of VC market negatively affects the rate of biotechnology start-up.

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 datasets are also discussed. Section 3 presents the results of empirical analyses. Section 4 concludes. Appendix explains how to construct the proxy of VC commitment.

2 Data Description

As measures of innovation, we use both TFP growth and patent count. It is interesting to study both of these innovation measures for the following reason. An important differences of TFP growth and patent is that TFP growth results from adopted new technology, whereas patents are still ideas about new technology and not necessarily adopted yet. Therefore, if VC investment is used for generating new technology ideas rather than adopting these ideas, we expect that the VC-first hypothesis to hold for patent counts but not for TFP growth. If VC investment is used for adopting the ideas instead of generating them, we expect that the VC-first hypothesis to hold for TFP growth but not for patent counts.

As measures of VC investments, we examine first round investments and follow-on round investments, separately. First round investments are often made to early-stage ventures and many of them eventually fail, whereas follow-on round investments are often made to later-stage ventures which are more likely to have proven their viability than early-stage ventures. As a consequence, when we test for the VC-first hypothesis, we expect that follow-on investments have bigger impacts on innovation than first round investments. When we test for the innovation-first hypothesis, we expect that it holds better for first round investments than follow-on round investments, because first round investment decisions are made mainly based on technological opportunities of the ventures, whereas follow-on round investment decisions are made based on other individual firm-specific factors such as how well they performed up to date.

We normalize VC investments using privately-funded industry R&D expenditure because the degree to which VC investment affects innovations may vary across industries.

In what follows, we detail how we construct the data set for the results. There are two major challenges in assembling this data set. The first challenge is concordance between venture capital data and TFP data. The second challenge is extending TFP data over the NBER coverage.

2.1 Data Sources

The data analyzed in this paper come from the four main data 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 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 records SIC codes of the companies that were financed from venture capitalists. However, this variable is very often missing. 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. As detailed in Ueda and Hirukawa (2008), for some observations, we find SIC codes either by merging with other data sources such as CRSP or by handcollection. Then, using the observations with SIC codes, both originally recorded and collected by us, we develop a bridge table between SIC codes and VEIC codes. According to this bridge table, we distribute the investment amount of the observations with which SIC is not recorded.

The NBER productivity database draws the original data from Bureau of Census and contains productivity related variables for all manufacturing industries at SIC 4-digit level.[4] The data are annual, start from 1958 and end in as early as 1996, which limits one from extending an analysis into recent years. In order to study the impact of rapid increases in VC investment in late 90s on TFP growth, we extend the NBER productivity database up to 2001 in the method described in the next section. The NBER productivity database covers only manufacturing. Thus, we limit our scope to manufacturing industries.

The NBER patent database and its extension contain[5] the information of utility patents granted

[4] Bartelsman and Gray (1996) gives detailed descriptions about this NBER productivity database.

[5] The extension is downloadable from the Bronwyn Hall's website (http://elsa.berkeley.edu/users/bhhall/bhdata.html).

at U.S. patent and trademark office (USPTO) from 1963 to 2002.[6] 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.[7]

The R&D database contains annual spending of R&D sorted by industry and by source of funding. As Kortum and Lerner (2001), we interpolate if numbers are missing due to the NSF's undisclosure policy. The R&D database's industry classification scheme roughly corresponds to SIC 2-digit. The name of each industry and corresponding SIC codes under the R&D database are written in Table 2. Hereafter, we call this industry classification system "KL classification", as Kortum and Lerner (2001) are also using this industry classification.

2.2 Extending the NBER productivity database and VC investment by KL classification industry

We *extend* the NBER productivity database and VC investment tabulated according to KL classification up to 2001. We pursue to extend the sample period up to 2001, in order to include the impact of unprecedented increases in VC investment in late 90s. In the subsection that follows, we describe how we extend the NBER productivity database. The method of extending VC investment data is described in Ueda and Hirukawa (2008).[8]

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

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

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

[8]For robustness check of our results, we also construct the proxy of VC commitment as an additional explanatory variable for VC investment The method of constructing this data item is described in the Appendix.

2.2.1 Extension and Modification of NBER Productivity Database

We use the five-factor (production labor hours, non-production workers, capital, energy and non-energy material) productivity as our measure of TFP.[9] The original NBER Manufacturing Productivity Database contains this TFP series up to 1996. To include later 90s period when the U.S. venture capital industry experienced an explosive growth in our study, we extend both TFP and capital expenditure series up to 2001.

Except for the calculation of labor costs as detailed later, we follow the same method as the NBER productivity database for extending the TFP series. (Bartelsman and Gray, 1996) We collect the dollar amount of shipment (output), energy expenditure, non-energy material cost, labor cost and capital expenditure, and production labor hours and non-production workers from the Annual Survey of Manufacturers ("ASM") by the Bureau of Census. The real capital stock is provided by the Federal Reserve Board. Deflators for shipment, energy expenditure and non-energy material cost are constructed using two types of data sources. The first type of data sources is the input-output flow tables that detail the composition of inputs and outputs (shipments) for each industry. For equipment and structure shipment, we use the 1997 version of Capital Flow Table from Bureau of Economic Analysis. For other types of shipment and energy and non-energy material, we use the 1997 Benchmark I-O use and make tables also from Bureau of Economic Analysis. The second type of data sources is price information of each commodity that constitutes inputs and outputs. We draw these price data from producer price index and consumer price index from Bureau of Labor Statistics. When we do not find an exact match of a commodity with the price index, we use the index of a closely related commodity.

The NBER Productivity Database is recorded on the 4-digit Standard Industry Classification

[9] The deflated value of shipment is defined as the real output, and five factors are the real capital stock, production worker hours, non-production workers, the deflated energy cost and the deflated non-energy material cost. Factor shares are calculated as the corresponding expenditures divided by the value of shipment, whereas the capital share as the residual so that the sum of shares is equal to one.

(SIC) System, whereas, for every dataset after 1996, the industry classification is based on the 6-digit North American Industry Classification System ("NAICS"). The KL industry classification is roughly speaking 2-digit SIC system. As the KL industry classification is coarser than the 4-digit SIC, up to 1996, we generate dollar figures based on the KL industry classification by aggregating dollar figures from the NBER Productivity Database. Productivity growth for each KL industry up to 1996 is computed as value added weighted average of productivity growth in the NBER Productivity database.

The KL industry classification is not always coarser than the 6-digit NAICS, that is, two establishments that share the same 6-digit NAICS may belong to different KL industries. To convert the 6-digit NAICS figures into those based on the KL industry classification, we first use the bridge table between 4-digit SIC and 6-digit NAICS as of 1997 published by the Bureau of Census. Number of employees and average number of production workers are converted by the bridge table for "Paid Employees." Annual payroll and production worker wages are converted by that of "Annual Payroll." All others are converted by that of "Sales, Receipts, or Shipments." The 4-digit SIC based figures constructed this way are further aggregated into the figures tabulated according to the KL industry classification.

There are two challenges in extending the productivity data beyond 1996. First, through the transition from SIC to NAICS in 1997, some industries classified as manufacturing until 1996 are no longer classified as manufacturing. Therefore, their data are no longer available in ASM. They are entire portions of SIC 2411 (Logging), 2711 (Newspapers), 2721 (Periodicals), 2731 (Book publishing), and 2741 (Miscellaneous publishing), and some portions of 2771 (Greeting cards) and 3732 (Boat building and repairing).[10] These industries all belong to "Others" in the KL industry

[10] In addition to the change from SIC to NAICS in 1997, there were a sequence of redefinitions in SIC in the years, 1972, 1977, and 1987. Data from some years are reallocated from one SIC 4-digit industry to another. We follow the method specified in Section 3.1 of Bartelsman and Gray (1996) and use the bridge tables that ASM reported for each of the redefinition years.

classification scheme and, as a consequence, we dropped "Others" from our analysis. Therefore, the original KL industry classification scheme contains twenty industries, whereas our analysis is focused on nineteen industries. Second, whereas the NBER database defines the new capital expenditures as "total capital expenditures", the latest ASM contains only the sum of new and used capital expenditures. Then, we compress each 4-digit SIC-based capital expenditures obtained above by the share of the industry's new capital expenditures to the total in 1996.

We also modify 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 consisted 10.8% of total pay 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 as a result would underestimate productivity growth, because labor input growth is slower than growth of other inputs. We obtain employer's social security contribution and fringe benefit from ASM.

2.3 Descriptive Statistics

Table 1 shows that VC investments in the U.S. manufacturing industry have dramatically grown during the last four decades, in terms of both dollar amounts and ratios to privately funded R&D expenditures. 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 venture capital, the investment amount significantly increased from 1970s to 1980s. These changes involve clarification of ERISA prudent man rule,[11] reduction of capital gains tax rate,[12] and introduction of Bayh-Dole Act that facilitated technology transfer from universities to private sectors.[13] The

[11] In 1978, the U.S. Department of Labor clarified that investments in venture capital funds by pension funds do not violate the "prudent man rule" in Employment Retirement Income Security Acts (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

whole VC industry experienced 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.

– Tables 1 and 2 Here –

Compared to the data used in Kortum and Lerner (2001), our venture capital investment figures are systematically large, even after taking into account the difference in constant dollar expressions.[14] This discrepancy happens probably because Venture Economics backfills their database. The backfilling creates a concern for a survivorship bias such that a higher fraction of older data points is investment made by successful and surviving venture capital funds. As venture capital investment has significantly increased in the end of 1990s, and the recent investment is likely to represent lower quality investment than earlier time, we may underestimate the effect of venture capital investment on innovations.

Table 2 shows VC investment tabulated into each industry. It is easy to see that VC investments are clustered. In particular, Drugs (KL 6), Office and Computing Machines (KL 13), Communication and Electronic (KL 15), and Professional and Scientific Instruments (KL 19) account for 83% of the total VC investment in the manufacturing industries to date.

– Table 3 (Panel A-D) Here –

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).

[14] Kortum and Lerner (2001) and this paper express venture capital investments in 1992 and 2001 constant dollars, respectively.

Table 3 shows the descriptive statistics of three variables examined in this paper. Panels A and B provide summary statistics of VC investment by industry in terms of dollar amount and the ratio to privately funded R&D expenditures. Comparing these two panels, one can see that VC investment in Office and Computing Machines is not only large in the absolute term but also so in the relative term, being for 9.55% of the industry R&D expenditures. Notably, VC investment in Textile and Apparel is the second largest in the relative term, although it is small in the absolute term. In other industries, the relative presence of VC investments are quite small and often it is less than one percent of industry R&D expenditures on average.

Panels C and D present summary statistics of two innovation measures, namely, annual TFP growth and the number of patent applications. We can see from Panel C that indicating a positive correlation between innovation and VC investments, TFP in the Office and Computing Machines industry has grown at as high as 11.3% on average. There is one caveat for interpreting this high number. 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. In 1980s, the Bureau of Census conducted the measurement of quality change in those industries with help of IBM. This is the only large-scale attempt made by the Bureau to incorporate quality improvement. For this reason, industries other than computer related ones may not exhibit substantial quality improvement in their TFP growth figures and they may be under-estimated.

Panel D demonstrates that the distribution of patent counts across industries is different from that of TFP growth. The Other Non-electrical Machinery industry dominates in patent counts, and the Professional and Scientific Instruments industry follows.

3 Empirical Methods and Results

In this section, we present the methods and the results of our empirical analyses. The underlying methods used here are panel AR regressions, studying forecasting powers of VC investments and the two innovation measures. We begin with examining the relation between VC investment and TFP growth and then proceed to study the relation between VC investment and patent count. Stated otherwise, our sample period is from 1968 to 2001.

3.1 Causality between VC Investments and TFP Growth

We are now going to explain our estimation model and present the results of our analysis on VC investment and TFP growth.

3.1.1 Panel AR Regressions

We borrow the idea to examine causality problems from Granger Causality. Granger causality test examines if X causes Y by regressing Y on the past realizations of X and Y and seeing if the series of X has any explanatory power. We apply this test to VC investment and TFP growth in panel. Let $TFP_{i,t}$ and $VC_{i,t}$ be TFP growth and the ratio of VC investment to privately funded R&D expenditures in industry i at time t. The representations of our causality test consist of estimating the following equations:

$$\begin{aligned}
TFP_{i,t} &= \alpha_0 + \sum_{l=1}^{L} \alpha_l VC_{i,t-l} + \sum_{l=1}^{L} \beta_l TFP_{i,t-l} + \boldsymbol{\lambda}'\mathbf{Z}_{i,t} + \eta_i + \epsilon_{i,t}, \text{ and} \quad (1) \\
VC_{i,t} &= \gamma_0 + \sum_{l=1}^{L} \gamma_l TFP_{i,t-l} + \sum_{l=1}^{L} \delta_l VC_{i,t-l} + \boldsymbol{\psi}'\mathbf{Z}_{i,t} + v_i + u_{i,t}, \quad (2) \\
i &= 1, \ldots, N; t = 1, \ldots, T,
\end{aligned}$$

where L is the maximum lag length, η_i and v_i are unobserved industry-specific heterogeneities, $\mathbf{Z}_{i,t}$ is a set of control variables, and $\epsilon_{i,t}$ and $u_{i,t}$ are idiosyncratic errors that are assumed to be mutually serially uncorrelated. In particular, we choose year dummies as the elements of $\mathbf{Z}_{i,t}$.

We also assume η_i and v_i to be *fixed effects* for two reasons. First, if the industry effect represents omitted variables, it is highly likely that these industry-specific characteristics are correlated with the other regressors. Second, it is not reasonable to view each of the manufacturing industries considered in this paper as a random sample from a much larger universe of industries.

No causality in Granger's sense from VC investment to TFP growth and from TFP growth to VC investment are hypothesized as $H_0 : (\alpha_1, \ldots, \alpha_L) = \mathbf{0}$ and $H_0' : (\gamma_1, \ldots, \gamma_L) = \mathbf{0}$, respectively. We perform the hypothesis testing for two different VC investment variables: the ratio to privately funded R&D expenditure of first-round investment and that of follow-on investment. Two different scenarios about lag are assumed. The first one contains two-year lag and the other contains four-year lag.

An econometric issue is that in our panel data the time dimension ($T = 34$, annually from 1968 to 2001) exceeds the industry dimension ($N = 19$). A common strategy of estimating (1) and (2) is to apply the linear generalized method of moments (GMM) estimation, either by taking first differences of these equations ("difference GMM" by Holtz-Eakin, Newey and Rosen, 1988, and Arellano and Bond, 1991) or by imposing additional moment conditions as well as those implied by first-difference transformations ("system GMM" by Arellano and Bover, 1995, and Blundell and Bond, 1998). However, these estimators are designed for "large N, small T" panels, unlike ours. Alternatively, for "large T, small N" panels like ours, we may transform the data in deviations from the industry-specific means and run the ordinary least squares (OLS). This strategy, known as fixed effects within group or least squares dummy variable (LSDV) estimation, is known to yield biased estimates if the time dimension is modest.[15] Since, it appears that there is no estimation strategy currently available that is well suitable to our panel data, we estimate (1) and (2) by LSDV, difference GMM, and system GMM and check the robustness. For both difference and

[15] Judson and Owen (1999) show that biases may be substantial even when the time dimension is as large as 20 to 30.

system GMM, we compute one-step estimators for inference.[16]

– Tables 4-A and 4-B Here –

Tables 4-A and 4-B present the estimation results for the equations (1) and (2), respectively. All standard errors are based on the heteroskedasticity-robust formula. Looking into specification testing results from the two GMM estimators, we find that the Arellano-Bond AR(1) test strongly rejects the null of no first-order serial correlation for (1), regardless of the VC investment measure or the lag length. The same test also rejects the null at the 5% level for (2) using the follow-on round VC investment. These results are not surprising. Because the Arellano-Bond test is applied to the residuals in differences, negative first-order serial correlation is expected due to the first-difference transformation before implementing GMM. Therefore, it is meaningful to check the presence of first-order serial correlation in levels using the results of the Arellano-Bond AR(2) test. Overall, the AR(2) test does not reject the null of no second-order serial correlation at the 5% level. The results from the two lag specification of (1) by the system GMM indicate a presence of second-order serial correlation, but this issue is resolved when the lag length is increased to four. In addition, most of Sargan statistics provide evidence of violating exogeneity in instruments at the 5% level; exceptions are all four results of (1) by the difference GMM and the result from the four lag specification of (1) using the first round VC investment by the system GMM.

Next, we examine the estimated coefficients. We can see from both tables that for each lag length and each measure of VC investments, estimated coefficients are qualitatively similar across three estimation methods. Both tables also show that coefficients on first-order autoregressive terms are

[16] One-step estimators are often found to be more reliable than two-step ones for inference purposes. See Arellano and Bond (1998), Blundell and Bond (1998), and Judson and Owen (1999), for instance. We do not run the two-step GMM to apply Windmeijer (2005) correction to the covariance matrix, solely because this is designed for "large N, small T" panels.

in general significantly positive, not surprisingly suggesting the presence of positive autocorrelation for both variables. An interesting observation is that in Table 4-B, estimated coefficients of the first-order autoregressive terms when the first round VC investment is used are considerably smaller than those when the follow-on VC investment is used. Indeed, there are some industries that exhibit weak serial dependence in the first round VC investment and strong dependence in the follow-on investment.[17] It seems that these industries are a main reason for the discrepancy in the size of the coefficients on first-order autocorrelation terms between two investment measures.

We then look into the testing results of Granger causality. We start from examining the results of testing the null of no Granger causality from VC investment to TFP growth in Table 4-A. This table shows that for each lag length and each estimation method, the Granger test rejects the null at the 5% level for the case of the first round VC investment, whereas it does not for the case of the follow-on investment. This result is surprising, given that the follow-on round investment is more likely to have immediate positive impacts on innovation than the first round VC investment.

The significance of the Granger test for the first round VC investment appears to be mainly due to significantly positive coefficients of two-year lagged VC investment. We can also see that coefficients on one-year lagged VC investment tend to be negative (although insignificant at the 5% level). This suggests that VC investment is associated with slowdown of TFP growth in the year following. One interpretation is that a rapid increase in VC investment is associated with a subsequent stock market crash and therefore recessions (Abreu and Brunnermeier, 2003). TFP is positively related to macro economic conditions because manufacturing plants are more efficiently utilized in economic booms than during recessions, and therefore TFP growth slows down when recessions happen.

[17] For example, first-order sample autocorrelations of the first and follow-on round VC investments (relative to privately funded R&D expenditures) are substantially different in the following five industries: KL 3 (-0.00 for the first round VC investment, 0.60 for the follow-on round VC investment); KL 7 (0.18, 0.62); KL 8 (0.22, 0.71); KL 10 (0.06, 0.61); and KL 14 (0.21, 0.71).

We now turn to Table 4-B, where we examine the results of testing the null of no Granger causality from TFP growth to VC investment. For the case of the first round VC investment, all Wald statistics other than the one from LSDV in the two-lag specification reject the null at the 5% level. On the other hand, for the case of the follow-on investment, when the lag length is two, all three Wald statistics are so small as not to reject the null at the 5% level. It may be the case that it is hard to detect the causality from TFP growth to VC investment over the time horizon of maximum two years. Once the lag length is increased to four, however, two GMM results strongly reject the null. These results may indicate that causality tests are sensitive to choices of lag length, as often reported. For both the first and the follow-on VC investment, the coefficients on one-year lagged TFP growth are positive. In addition, as we expect, a strong positive causality from TFP to VC investments seems to exist especially for the first round case (but not strong for the follow-on case), in that the coefficients are often significant for the first round.

To summarize, we find some evidence to support the innovation-first hypothesis; Past TFP growth is positively related with both the first and the follow-on round VC investment. This evidence is stronger for the first round VC investment as predicted. We also find that the first-round VC investment is positively and significantly related with TFP growth in two years, supporting the VC-first hypothesis. Nevertheless, both the first and the follow-on VC investment are negatively related with TFP growth in one year. This negative relation may arise from the cycle of crashes following bubbles.

3.1.2 Industry Analysis

So far we have examined the relationship between TFP growth and VC investment using the panel AR. The panel analysis gives us a general idea about how TFP growth and VC investment are related in the manufacturing industry as a whole. The problem is however that the regression coefficients pick up both cross sectional and time series effects, and we cannot separate these two for the purpose of interpreting the coefficients. Since the degree to which VC investment affects TFP growth is likely to differ across industries, we now examine the relation between VC investment and TFP growth for each industry individually. We focus on the following top five industries in terms of dollar amounts of VC investment: Drugs (KL 6); Office and Computing Machines (KL 13); Communication and Electronic (KL 15); Other Electrical Equipment (KL 16); and Professional and Scientific Instruments (KL 19). These industries must be of particular interest in terms of assessing the interactions between VC investments and innovations, because they account for 88% of the total VC investment in manufacturing industries to date.

To do the industry analysis, we introduce two new variables. First, we control for the industry capacity utilization when TFP growth is the dependent variable.[18] The construction of the TFP series assumes that capital is fully utilized. Nevertheless, this assumption is not satisfied when the industry is in recession. As a result, TFP tends to be underestimated during recessions. By controlling for capacity utilization, we attempt to lessen the mismeasurement problem of TFP. Second, for the equation (2), we control for the policy changes that took place in 1979 and presumably stimulated the U.S. VC industry. One of the changes concerns the supply side of VC investments. Before 1979, most pension funds had refrained from investing in VC not to violate "prudent man rule" in the US. Department of Labor of the Employment Retirement Income Security Acts (ERISA). In 1978, the Department of Labor clarified VC as a possible investment target for pension funds and in 1979, this clarification was implemented. This clarification is considered to have made it substantially easier for VC to raise funds since each VC organization is typically small and does not have an own mean to raise a large amount of funds directly from original investors. Another change

[18] The data source of capacity utilization is Federal Reserve Bank, Board of Governors. The capacity utilization data is described in NAICS. We have matched with the KL code as follows. Note that the numbers in the parentheses are associated NAICS). KL 1 (311, 312), KL 2 (313,314,and 315); KL 3 (321, 337), KL 4 (322), KL 5-7 (325), KL 8 (211, 213, 324); KL 9 (326), KL 10 (327), KL 11 (331), KL 12 (332), KL 13 (3341), KL 14 (333), KL 15 (3342), KL 16 (335), KL 17 (G3361T3), KL 18 (G3364T9), KL 19 (334), and KL 20 (316,323,339). The correlation coefficient between TFP growth and capacity utilization is 0.11 with p-value 0.01.

is associated with the demand side of venture capital investments. In 1979, the highest marginal capital gains tax rate was reduced from 33.8% to 28%. Entrepreneurs backed by venture capital investments typically cash in on their own created firms by selling their stakes to third parties. These incomes are subject to capital gains tax. Thus, the reduction of capital gains tax rate presumably encourages entrepreneurship and enhances the demand for venture capital investments. To control for the impact of this policy changes on VC investment, we construct the dummy variable which takes zero until 1979 and takes one otherwise. We call this variable ERISA dummy.[19]

– Tables 5-A and 5-B Here –

Tables 5-A and 5-B present the estimation results of the first and follow-on round VC investments as either dependent or independent variable, respectively. All regressions include four-year symmetric lags of two variables and up to a quadratic time trend. For the VC investment regression, results with and without the ERISA dummy are reported. In addition, for the TFP regression, results with and without the industry capacity utilization are reported. Note that coefficients on autoregressive terms are not reported. All standard errors are based on the heteroskedasticity-robust formula.

We look into the results industry-by-industry.

In the Drugs industry, TFP growth exhibits a convex and decreasing trend no matter which the first or the follow-on round VC investment is used. The first round VC investment also has a convex trend, which is not significant in the follow-on investment. The Granger test using the follow-on round investment is consistent with the VC-first hypothesis, but none of coefficients on lagged VC investments in this regression is significant. This result does not come as a surprise. In

[19] Correlation coefficients (p-values) between ERISA and two VC investment measures are 0.21(0.00) for the first round VC investment relative to private R&D expenditures, and 0.27(0.00) for the follow-on round VC investment relative to private R&D expenditures, respectively.

the drugs industry, most of technological innovations come as improvement in the quality of drugs. Nevertheless, such improvement is difficult to measure and therefore TFP growth is unlikely a good measure of innovation. Further, drug development is a long process and therefore VC investments may have a positive impact on TFP growth after four years.

In the Office and Computing Machines industry, the estimated coefficients on the capacity utilization and the ERISA dummy are positive in both tables, as predicted, and they are often significant. The results of the Granger test provide no strong evidence of the causality between TFP growth and VC investments. The estimated coefficients on one-year lagged TFP growth in both VC regressions are positive consistent with the innovation-first hypothesis, whereas those on one-year lagged VC investment in both TFP regressions are negative. None of these coefficients are significant at the 5% level.

In the Communication and Electronic industry, TFP growth exhibits a negative and convex trend. The signs of the coefficients on the capacity utilization and the ERISA dummy are both positive as expected, but they are mostly insignificant. The Granger test strongly suggests both ways of causality, no matter which the first or the follow-on round VC investment is used. The coefficients on one-year lagged VC investments in the TFP regressions are significantly negative. Although the Granger test strongly supports the causality from VC to innovation in this industry, VC investment appears to slow down TFP growth in the year following, similar to the results of the panel regression. In contrast, the positive and significant coefficients on four-year lagged TFP growth in VC regressions are consistent with the innovation-first hypothesis. A puzzling finding is that estimated coefficients on one- to three-year lagged TFP growth in the follow-on VC regression are all negative.

In the Other Electrical Equipment industry, we can merely find that coefficients on the capacity utilization are significantly positive. There is little evidence of causality in either way.

In the Professional and Scientific Instruments industry, TFP growth seems to follow a negative trend. The coefficients on the capacity utilization are again significantly positive as expected. But, the Granger test does not suggest causality in either direction.

Combining the results of all manufacturing industries in previous sections, we can point out that the results from the Communication and Electronic industry confirm us the validity of the innovation-first hypothesis at the entire manufacturing industry level. In particular, the significantly positive coefficients on four-year lagged TFP growth in the follow-on VC equation appear to come from this industry's results. On the other hand, the same Communication and Electronic industry provide supporting evidence that VC investment predicts TFP growth slowdown in one year at the entire manufacturing industry level for the first round VC case.

3.2 Causality between VC Investments and Patent

We are now going to use the number of patent applications that were eventually granted as the measure of innovation, and redo the same analyses as in the previous two sections.

3.2.1 Panel AR Regressions

– Tables 6-A and 6-B Here –

We rerun the panel AR regressions (1) and (2) by replacing $TFP_{i,t}$ with the logarithm of patent counts, i.e. $\ln(Patent_{i,t})$, and perform the Granger causality test. The results in Tables 6-A and 6-B correspond to those in Tables 4-A and 4-B, respectively. All standard errors are based on the heteroskedasticity-robust formula. Again, the estimated coefficients are robust across three different estimation methods. The coefficients on first-order autoregressive terms are significantly positive. The results from the Arellano-Bond AR(2) test are acceptable in general; the only exception is the 1% significance when the four lag specification of the patent regression is estimated by the system GMM. On the other hand, all Sargan tests suggest possible misspecification of the models.

We now look into the testing results of Granger causality. A major difference from the results using TFP growth is that when the first round VC investment is used, neither the VC- nor innovation-first hypothesis is supported. Note that all coefficients on one-year lagged VC investment and patent counts are positive but insignificant. On the other hand, for the case of the follow-on VC investment, the VC-first hypothesis is strongly supported over the four-year time span. Nevertheless, the one-year lagged follow-on VC investment is significantly and negatively related with patent, suggesting that follow-on VC investments slow down patenting activities in the subsequent year. Interestingly, the negative impact of the follow-on investment on innovation in the following year is common, whether innovation may be measured by TFP growth or patent counts. The Granger test from the follow-on VC regression also indicates the possibility of the innovation-first hypothesis, but none of coefficients on lagged patent counts are significant at the 5% level (although positive in general).

To summarize, for the first round VC investment, we do not find any support for the causality between VC investment and patent counts. For the follow-on round VC investment, our results support the VC-first hypothesis over the four-year horizon. But the negative impact of the follow-on round VC investment on patent count casts doubt on the validity of VC-first hypothesis.

3.2.2 Industry Analysis

For the same five industries as used in Section 3.1.2, we run VC and patent regressions. The ERISA dummy is still used as a control variable for the VC regression. For the patent regression, we introduce a new control variable. There are two changes on patent policies in early 1980's, namely, the introduction of Bayh-Dole Act in 1980 and the establishment of Federal Circuit Patent Court in 1982. The former change allowed to patent innovations funded by federal grants. The latter change made it easier to enforce patent rights. Therefore, after these changes, we expect that patent propensity went up. To see if controlling the impact of these policy changes increases the explanatory power of patent counts, we construct the dummy variable which takes zero until 1980 and takes one otherwise. We call this variable D1981.[20]

– Tables 7-A and 7-B Here –

Tables 7-A and 7-B present the estimation results of the first and follow-on round VC investments as either dependent or independent variable, respectively. Again all regressions include four-year symmetric lags of two variables and up to a quadratic time trend. The same specifications as before are considered for the VC regression, whereas results with and without the dummy variable D1981 are reported for the patent regression. Coefficients on autoregressive terms are not reported. All standard errors are based on the heteroskedasticity-robust formula.

Overall, the results from the patent regressions support that VC investments predict future patenting, no matter which the first or the follow-on round VC investment is used. Exceptions are the Drug industry for the first round case and the Other Electrical Equipment industry for the follow-on case; actually, in the the latter case, none of coefficients of lagged VC investments is significant. Interestingly, whenever the causality from VC to patent is significant, negative coefficients on one-year lagged VC investment contributes to the significance of the Granger test; again, it appears that VC investment slows down innovation in the year following. In addition, whenever the coefficient of D1981 is significant, it is negative, as opposed to our expectation; see Other Electrical Equipment in both tables and Professional and Scientific Instruments in Table 7-A. In contrast, the results do not provide evidence of the causality from innovation to VC investment in general. The only exception is significantly negative coefficients on one-year lagged patent counts for the follow-on VC case in the Professional and Scientific Instruments industry.

[20] The correlation coefficient between patent counts and D1981 is 0.13 with p-value 0.00.

To summarize, when patent counts are chosen as a measure of innovation, the causality from VC investment to innovation is largely supported at individual industry levels. However, as opposed to the VC-first hypothesis, VC investment appears to slow down the innovation measure one year later.

3.3 Robustness Check

We run two types of robustness checks. One is to normalize VC investment by capital expenditure instead of R&D and the other is to include "available fund for VC investment" as an explanatory variable for VC investment. (See Appendix for how to construct the variable "available fund for VC investment.") Testing results are qualitatively similar to those reported in this section.

4 Concluding Remarks

This paper has examined both ways of the causality between innovation and venture capital investment using a framework similar to the Granger causality test. For this purpose, we studied a panel of U.S. manufacturing industries. The panel AR analyses have shown that the results on causality vary across our choices of measures of VC investment and innovation.

We find some evidence of the innovation-first hypothesis if TFP growth is used as the measure of innovation. The causality from TFP growth runs to both the first and the follow-on round VC investment. We find weak support for the VC-first hypothesis if TFP growth is used as the measure of innovation. Two-year lagged first round VC investment is positively related with TFP growth. Nevertheless, one-year lagged first round VC investment is negatively related with TFP growth suggesting the presence of a bubble-crash cycle.

When patent counts are used as the measure of innovation, we find little evidence of both the innovation-first and the VC-first hypotheses. Nevertheless, we find that both the first and the follow-on round VC investment often predict lower patent counts one year later at individual industry levels. This result is consistent with Engel and Keilbach (2007) and Caselli, Gatti and Perrini (2008) that find significant slowdown of patenting activities once patenting firms obtain VC funding.

These results suggest that the time-series relation between VC investments and innovations is not as simple as we thought. Consistent with the innovation-first hypothesis, lagged TFP growth is positively related with VC investment but not with patent count. The VC-first hypothesis has only weak support. Rather, we often find that VC investment leads slow-down of TFP growth and patenting activity.

Appendix: Construction of Available Fund for Venture Capital Investment

We employ the amount of funds available for venture capital investment as an additional explanatory variable for venture capital investments. Due to a high transaction cost, venture capital firms raise funds infrequently - every few to several years. And thus, the amount of funds available for venture capitalists to invest is restricted by the difference in the amount of funds raised and the amount of funds disbursed, at least for the short run. We call this difference "available fund." Here, we describe how we constructed this dataset.

VentureXpert provides the amount of funds raised most of time. However, how much of the funds was disbursed is not well recorded. If it is recorded, the total syndicated amount of disbursement is recorded but the amount of individual contribution is not available. Thus, we estimate how the funds were disbursed in the following manner. We take four steps in constructing the commitment for each VC fund: (i) estimating years of disbursement, (ii) estimating the annual amount of disbursement over years of disbursement, (iii) allocating the annual amount of disbursement according to "industry preferences" of each fund, and (iv) reclassifying the amount assigned to each industry each year from VEIC to KL classification.

In the first step, we primarily define as "the disbursement life" for each fund the period from the earlier of establishment year or the year of first investment, to liquidation year, as far as the variable liquidation year is recorded. We do not define each fund's establishment year as the beginning of the life, because VentureXpert sometimes records the funds that "started" their first investments earlier than their establishments and those without establishment year but with investment history. For funds without liquidation year, we define the greater of the length of disbursement, which is the duration between the first disbursement episode and the last, and five years as the disbursement life. Some fund have establishment year but no investment history recorded. For such funds, we simply set their disbursement life equal to five, and thus we “assign” five years after establishment as the end of the life.

In the second step, we estimate the annual amount of disbursement for each year of the disbursement life by using annual total VC disbursements as weights. For funds that, we estimate, continue disbursement beyond 2002, we also prepare point forecasts of the disbursements by fitting a simple time series model.[21] We call the difference between fund size and accumulated disbursement that we estimate, the fund's “available capital” in the year.

In the third step, we assume that each fund's portfolio companies represent the fund's preferences on industries and that their preferences remain unchanged over the disbursement life. Although VentureXpert records “Firm Industry Preference” data as well, it is often hard to find an exact match of the data to VEIC: how can we find an exact match to VEIC if a fund's industry preference is expressed as “Diversified” or “High Tech”? Alternatively, VentureXpert records VEIC for each portfolio company, and thus we do not encounter such difficulty. Then, for each fund we allocate available capital in each year to all industries preferred by using the corresponding actual disbursements as weights. Some funds have no investment history, and thus no portfolio companies. For these funds, we assume that they have no particular industrial preferences. Then, for each of all such funds we allocate available capital in each year over all industries disbursed in the year by using actual disbursements as weights.[22]

To construct the available fund in the way described above, we examine all VC funds that were established from 1960 to 2002 and focus on investing in the U.S. companies. We drop those without fund size data from our sample. The funds eliminated in this screening are typically those established before mid 80's, and include 3i Capital and ABS Ventures, for example. Nonetheless,

[21] We fit ARIMA$(2, 1, 2)$ to the logarithm of VC disbursements.

[22] This method is also used for the cases in which a fund has portfolio companies but no actual disbursements in these industries are recorded in some year during the life.

the number of funds remaining in our sample is 4,787 which accounts for nearly two thirds of all such funds.[23] Then, in the final step, we obtain the KL-classified available fund data in constant dollars by aggregating all available capitals over each KL classification in each year and deflating them.

[23] We also eliminate funds that has fund size but neither establishment year nor investment history.

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Table 1: Summary Statistics by Year

Venture capital investments refer to 2001 constant million dollar amount that venture capital funds invested in U.S. companies of each industry and in each year. "First Round" refers to venture capital investments made in companies that have never received venture capital financing before. "Follow-on Round" refers to venture capital investments made in companies that have received venture capital financing before. "R&D" refers to privately funded R&D expenditure. "TFP Growth" is value-added weighted average over 19 manufacturing industries. All others are sum of industry-level numbers.

				VC investment ($M)			VC investment/R&D		
Year	TFP Growth	Number of Patent Applications	Number of Firms Receiving VC Funding	Total	First Round	Follow-on Round	Total	First Round	Follow-on Round
1968	1.67%	42,436	25	58	56	2	0.14%	0.13%	0.00%
1969	0.36%	43,455	71	258	238	20	0.58%	0.53%	0.05%
1970	-1.69%	42,949	67	159	80	79	0.36%	0.18%	0.18%
1971	2.16%	42,631	68	344	225	119	0.77%	0.50%	0.27%
1972	2.89%	39,713	59	278	134	144	0.59%	0.29%	0.31%
1973	2.03%	40,008	66	335	163	172	0.67%	0.33%	0.34%
1974	-0.62%	39,113	45	125	66	59	0.25%	0.13%	0.12%
1975	-2.39%	39,268	42	147	46	101	0.30%	0.09%	0.20%
1976	2.79%	38,689	44	108	47	61	0.21%	0.09%	0.12%
1977	1.57%	37,984	65	187	75	112	0.34%	0.14%	0.21%
1978	1.16%	36,851	125	356	191	165	0.62%	0.33%	0.29%
1979	1.01%	36,309	179	490	218	272	0.81%	0.36%	0.45%
1980	-0.71%	36,294	254	900	485	416	1.44%	0.77%	0.66%
1981	0.50%	34,472	467	1,827	888	938	2.78%	1.35%	1.43%
1982	0.04%	34,287	578	2,263	643	1,621	3.23%	0.92%	2.32%
1983	2.04%	32,283	760	3,926	1,003	2,922	5.26%	1.34%	3.92%
1984	1.62%	33,990	844	3,922	941	2,981	4.82%	1.15%	3.66%
1985	0.90%	35,330	826	3,396	692	2,704	3.95%	0.80%	3.14%
1986	-0.03%	36,389	809	3,619	801	2,818	4.10%	0.91%	3.19%
1987	3.43%	39,626	878	3,420	791	2,629	3.93%	0.91%	3.02%
1988	0.94%	43,872	799	3,231	723	2,507	3.66%	0.82%	2.84%
1989	-0.69%	46,897	758	2,952	764	2,189	3.29%	0.85%	2.44%
1990	-0.40%	49,727	649	2,397	555	1,842	2.73%	0.63%	2.10%
1991	-0.68%	50,411	529	1,630	272	1,358	1.85%	0.31%	1.54%
1992	2.72%	53,586	571	2,668	728	1,940	3.00%	0.82%	2.18%
1993	0.99%	56,566	471	2,041	629	1,413	2.41%	0.74%	1.67%
1994	2.83%	63,527	451	2,075	686	1,389	2.39%	0.79%	1.60%
1995	2.33%	76,360	603	3,198	1,151	2,047	3.42%	1.23%	2.19%
1996	1.58%	72,481	736	3,897	1,219	2,678	3.86%	1.21%	2.65%
1997	1.95%	85,448	902	5,478	1,685	3,793	5.04%	1.55%	3.49%
1998	0.40%	84,124	1,144	6,385	1,713	4,672	5.91%	1.58%	4.32%
1999	2.73%	86,638	983	10,853	2,621	8,232	10.89%	2.63%	8.26%
2000	1.82%	84,483	1,384	22,666	5,475	17,191	21.10%	5.10%	16.00%
2001	-1.01%	73,072	1,081	12,312	2,584	9,727	11.92%	2.50%	9.41%

Table 2

Venture capital investments for U.S. manufacturing industries, by industry (millions of 2001 dollars). Venture capital investments refer to the million dollar amount that venture capital funds invested in U.S. companies of each industry and in each year.

	Industry	*SIC Codes*	*1968-69*	*1970-74*	*1975-79*	*1980-84*	*1985-89*	*1990-94*	*1995-99*	*2000-01*	*Total*
1	Food and kindred	20	0	21	8	35	339	246	345	80	1,073
2	Textile and apparel	22,23	1	20	18	28	100	303	270	187	929
3	Lumber and furniture	24,25	3	0	11	11	116	77	160	65	443
4	Paper	26	4	1	1	4	22	105	156	54	347
5	Industrial chemicals	281,282,286	22	2	4	174	308	218	223	164	1,114
6	Drugs	283	4	26	125	540	1,231	1,878	4,900	4,661	13,364
7	Other chemicals	284,285,287-289	0	14	8	10	113	69	161	138	513
8	Petroleum refining and extraction	13,29	13	11	91	562	164	59	954	452	2,306
9	Rubber products	30	0	21	34	41	78	128	308	297	907
10	Stone, clay and glass products	32	0	32	1	71	148	41	113	190	596
11	Primary metals	33	0	13	9	38	45	85	305	212	708
12	Fabricated metal products	34	6	15	20	30	58	82	131	242	584
13	Office and computing machines	357	77	501	402	6,184	5,611	1,646	4,274	5,319	24,016
14	Other non-electrical machinery	351-356,358-359	75	20	14	436	499	497	602	544	2,688
15	Communication and electronic	366,367	80	392	222	3,084	3,889	1,820	9,300	14,403	33,189
16	Other electrical equipment	361-365,369	13	47	103	198	470	543	1,265	2,285	4,923
17	Transportation equipment	371,373-375,379	1	11	11	39	186	244	274	193	958
18	Aircraft and missiles	372,376	0	0	1	10	79	64	59	59	271
19	Professional and scientific instruments	38	17	91	206	1,343	3,163	2,708	6,008	5,432	18,968
	Total		317	1,240	1,287	12,838	16,618	10,811	29,812	34,978	107,900

Table 3

Dollar amount and the ratio to privately funded R&D expenditures of venture capital investments for U.S. manufacturing industries, by industry.

Panel A: Venture Capital Investment (in millions of 2001 dollars)

	Industry	Mean	Median	Minimum	Maximum	Std. Dev.
1	Food and kindred	31.56	19.44	0.00	120.31	33.40
2	Textile and apparel	27.32	9.99	0.00	144.94	35.25
3	Lumber and furniture	13.04	7.05	0.00	66.88	16.82
4	Paper	10.21	1.89	0.00	61.73	17.94
5	Industrial chemicals	32.77	31.11	0.00	100.61	29.40
6	Drugs	393.07	160.50	0.00	2890.29	621.11
7	Other chemicals	15.10	6.23	0.00	86.66	19.52
8	Petroleum refining and extraction	67.84	22.09	0.00	461.47	101.08
9	Rubber products	26.68	9.06	0.00	189.20	39.29
10	Stone, clay and glass products	17.54	8.88	0.00	106.91	23.89
11	Primary metals	20.82	4.42	0.00	130.01	32.42
12	Fabricated metal products	17.19	8.10	0.00	205.03	35.51
13	Office and computing machines	706.35	360.26	12.26	3902.99	818.34
14	Other non-electrical machinery	79.05	77.32	0.00	275.07	72.47
15	Communication and electronic	976.15	400.71	22.20	9530.68	1855.40
16	Other electrical equipment	144.80	64.49	0.49	1550.87	291.52
17	Transportation equipment	28.18	13.98	0.00	107.21	34.20
18	Aircraft and missiles	7.98	0.41	0.00	77.00	15.62
19	Professional and scientific instruments	557.89	461.15	5.52	3142.02	703.93

Panel B: Venture Capital Investment/Privately Funded R&D

	Industry	Mean	Median	Minimum	Maximum	Std. Dev.
1	Food and kindred	1.81%	1.30%	0.00%	6.45%	1.82%
2	Textile and apparel	8.08%	4.07%	0.00%	43.99%	11.10%
3	Lumber and furniture	4.51%	2.25%	0.00%	25.13%	5.84%
4	Paper	0.61%	0.16%	0.00%	4.23%	0.97%
5	Industrial chemicals	0.60%	0.53%	0.00%	1.83%	0.55%
6	Drugs	3.89%	2.89%	0.00%	21.97%	4.88%
7	Other chemicals	0.58%	0.30%	0.00%	2.73%	0.67%
8	Petroleum refining and extraction	4.85%	0.83%	0.00%	70.59%	12.70%
9	Rubber products	1.73%	0.87%	0.00%	8.43%	1.98%
10	Stone, clay and glass products	2.06%	1.32%	0.00%	12.30%	2.67%
11	Primary metals	3.03%	0.34%	0.00%	21.14%	5.36%
12	Fabricated metal products	1.27%	0.62%	0.00%	12.22%	2.15%
13	Office and computing machines	9.55%	4.56%	0.36%	73.50%	14.92%
14	Other non-electrical machinery	1.74%	1.69%	0.00%	5.42%	1.44%
15	Communication and electronic	5.72%	4.28%	0.41%	38.66%	7.56%
16	Other electrical equipment	3.79%	2.08%	0.01%	40.76%	7.20%
17	Transportation equipment	0.21%	0.13%	0.00%	0.90%	0.23%
18	Aircraft and missiles	0.13%	0.01%	0.00%	0.98%	0.25%
19	Professional and scientific instruments	6.37%	5.00%	0.28%	28.91%	7.04%

Table 3 (Continued)

TFP growth and the number of patent applications for U.S. manufacturing industries, by industry. TFP growth for each industry is value-added weighted average of SIC four digit level TFP growth.

Panel C: TFP Growth

	Industry	Mean	Median	Minimum	Maximum	Std. Dev.
1	Food and kindred	0.56%	0.58%	-2.86%	3.73%	1.36%
2	Textile and apparel	0.72%	0.58%	-3.80%	3.73%	1.45%
3	Lumber and furniture	0.11%	0.16%	-3.25%	3.62%	1.75%
4	Paper	0.48%	0.61%	-4.36%	4.47%	2.19%
5	Industrial chemicals	0.72%	0.93%	-11.38%	7.08%	3.86%
6	Drugs	-0.23%	-0.19%	-5.03%	8.29%	2.90%
7	Other chemicals	0.23%	0.20%	-4.19%	8.42%	2.61%
8	Petroleum refining and extraction	0.52%	0.79%	-9.77%	8.73%	4.14%
9	Rubber products	1.05%	1.22%	-4.05%	4.51%	2.13%
10	Stone, clay and glass products	0.69%	0.56%	-2.57%	4.73%	1.94%
11	Primary metals	0.55%	0.94%	-7.68%	5.30%	2.46%
12	Fabricated metal products	0.24%	0.17%	-3.32%	3.96%	1.96%
13	Office and computing machines	11.29%	12.10%	-1.60%	24.72%	7.08%
14	Other non-electrical machinery	-0.09%	-0.05%	-5.22%	5.34%	2.41%
15	Communication and electronic	5.50%	3.25%	-2.92%	28.29%	7.12%
16	Other electrical equipment	0.88%	1.35%	-4.19%	4.46%	2.21%
17	Transportation equipment	0.50%	0.41%	-4.85%	6.53%	2.48%
18	Aircraft and missiles	0.22%	-0.02%	-5.63%	6.07%	2.83%
19	Professional and scientific instruments	0.72%	0.47%	-2.82%	4.73%	1.81%

Panel D: Number of Patent Applications

	Industry	Mean	Median	Minimum	Maximum	Std. Dev.
1	Food and kindred	433	419	305	644	91
2	Textile and apparel	530	467	343	872	161
3	Lumber and furniture	799	720	466	1,265	244
4	Paper	575	517	375	915	167
5	Industrial chemicals	2,803	2,827	2,166	3,872	353
6	Drugs	1,650	1,052	500	5,316	1,324
7	Other chemicals	2,048	1,816	1,526	3,425	503
8	Petroleum refining and extraction	295	293	219	385	37
9	Rubber products	3,186	2,920	2,269	4,721	725
10	Stone, clay and glass products	739	682	518	1,113	180
11	Primary metals	586	565	407	891	127
12	Fabricated metal products	3,580	3,466	2,547	4,909	691
13	Office and computing machines	3,681	1,542	1,250	12,439	3,644
14	Other non-electrical machinery	11,278	11,292	8,135	14,337	1,769
15	Communication and electronic	4,558	2,952	2,403	11,274	2,928
16	Other electrical equipment	4,083	3,523	2,638	7,304	1,466
17	Transportation equipment	1,484	1,494	883	2,203	375
18	Aircraft and missiles	226	222	146	308	42
19	Professional and scientific instruments	7,151	4,910	4,295	14,163	3,473

Table 4-A: Testing for VC-first Hypothesis on TFP growth

Does venture capital investment cause innovation? Dependent variables are TFP growth. Independent variables are lagged terms of various measures of venture capital investments and lagged TFP growth. Sample period is 1970-2001 (2 lags) or 1972-2001 (4 lags). "First Round" refers to venture capital investments made in companies that have never received venture capital financing before. "Follow-on Round" refers to venture capital investments made in companies that have received venture capital financing before. "R&D" refers to privately funded R&D expenditure. Estimation results from least squares dummy variable (LSDV), one-step difference GMM (D-GMM), and one-step system GMM (S-GMM) estimation are presented. Coefficients on time dummies are not reported. Estimates with *, **, and *** are significant at 10%, 5%, and 1% level. Heteroskedasticity robust standard errors are in parentheses. The null hypothesis for Granger-causality test is that all coefficients on venture capital investments are zero.

Dependent Variable = TFP growth

	Lag = 2			Lag = 4		
Independent Variable	**LSDV**	**D-GMM**	**S-GMM**	**LSDV**	**D-GMM**	**S-GMM**
First round VC/R&D(-1)	-0.0043	-0.0115	-0.0032	-0.0095	-0.0187	-0.0159
	(0.0325)	(0.0361)	(0.0271)	(0.0336)	(0.0436)	(0.0344)
First round VC/R&D(-2)	0.1095 ***	0.1037 **	0.1049 ***	0.1225 ***	0.1150 **	0.1130 ***
	(0.0419)	(0.0499)	(0.0391)	(0.0387)	(0.0500)	(0.0417)
First round VC/R&D(-3)				-0.0639	-0.0733 *	-0.0667
				(0.0585)	(0.0402)	(0.0552)
First round VC/R&D(-4)				-0.0268	-0.0373	-0.0311
				(0.0606)	(0.0577)	(0.0488)
TFP growth(-1)	0.2616 ***	0.2467 ***	0.3806 ***	0.2321 ***	0.2303 **	0.3401 ***
	(0.0786)	(0.0887)	(0.0723)	(0.0796)	(0.0900)	(0.0686)
TFP growth(-2)	-0.0500	-0.0639	0.0576	-0.0967	-0.0972	-0.0179
	(0.0726)	(0.0811)	(0.1142)	(0.0705)	(0.0790)	(0.1083)
TFP growth(-3)				0.0205	0.0195	0.0981 **
				(0.0732)	(0.0354)	(0.0500)
TFP growth(-4)				0.1213	0.1210	0.1673 **
				(0.0874)	(0.0858)	(0.0737)
Arellano-Bond AR(1) Test: p-value		0.01	0.01		0.01	0.01
Arellano-Bond AR(2) Test: p-value		0.29	0.03		0.50	0.57
Sargan Test: p-value		0.13	0.05		0.34	0.10
Granger-Causality Test:						
Wald Statistic	6.84	9.58	8.27	10.81	18.10	18.66
p-value	(0.03)	(0.01)	(0.02)	(0.03)	(0.00)	(0.00)

Dependent Variable = TFP growth

	Lag = 2			Lag = 4		
Independent Variable	**LSDV**	**D-GMM**	**S-GMM**	**LSDV**	**D-GMM**	**S-GMM**
Follow-on round VC/R&D(-1)	-0.0348	-0.0351	-0.0102	-0.0510	-0.0508 *	-0.0361
	(0.0408)	(0.0254)	(0.0335)	(0.0425)	(0.0288)	(0.0296)
Follow-on round VC/R&D(-2)	-0.0031	-0.0077	0.0365	0.0011	-0.0026	0.0024
	(0.0594)	(0.0528)	(0.0508)	(0.0564)	(0.0577)	(0.0436)
Follow-on round VC/R&D(-3)				-0.0266	-0.0282	0.0401
				(0.0382)	(0.0281)	(0.0327)
Follow-on round VC/R&D(-4)				-0.0467	-0.0476	0.0034
				(0.0604)	(0.0676)	(0.0658)
TFP growth(-1)	0.2650 ***	0.2575 ***	0.3888 ***	0.2348 ***	0.2329 ***	0.3437 ***
	(0.0785)	(0.0844)	(0.0730)	(0.0791)	(0.0876)	(0.0673)
TFP growth(-2)	-0.0415	-0.0479	0.0661	-0.0879	-0.0886	-0.0131
	(0.0733)	(0.0931)	(0.1258)	(0.0704)	(0.0828)	(0.1169)
TFP growth(-3)				0.0178	0.0167	0.1009 **
				(0.0727)	(0.0322)	(0.0467)
TFP growth(-4)				0.1280	0.1268	0.1768 **
				(0.0869)	(0.0837)	(0.0700)
Arellano-Bond AR(1) Test: p-value		0.01	0.01		0.01	0.01
Arellano-Bond AR(2) Test: p-value		0.22	0.04		0.37	0.55
Sargan Test: p-value		0.06	0.01		0.23	0.04
Granger-Causality Test:						
Wald Statistic	0.91	3.05	0.76	3.61	4.68	2.84
p-value	(0.63)	(0.22)	(0.68)	(0.46)	(0.32)	(0.58)

Table 4-B: Testing for Innovation-First Hypothesis on TFP Growth

Does innovation cause venture capital investment? Dependent variables are various measures of venture capital investments. Independent variables are lagged TFP growth and lagged terms of various measures of venture capital investments. Sample period is 1970-2001 (2 lags) or 1972-2001 (4 lags). "First Round" refers to venture capital investments made in companies that have never received venture capital financing before. "Follow-on Round" refers to venture capital investments made in companies that have received venture capital financing before. "R&D" refers to privately funded R&D expenditure. Estimation results from least squares dummy variable (LSDV), one-step difference GMM (D-GMM), and one-step system GMM (S-GMM) estimation are presented. Coefficients on time dummies are not reported. Estimates with *, **, and *** are significant at 10%, 5%, and 1% level. Heteroskedasticity robust standard errors are in parentheses. The null hypothesis for Granger-causality test is that all coefficients on TFP growth are zero.

Dependent Variable = First round VC/R&D

	Lag = 2			Lag = 4		
Independent Variable	**LSDV**	**D-GMM**	**S-GMM**	**LSDV**	**D-GMM**	**S-GMM**
TFP growth(-1)	0.0415	0.0416 ***	0.0468 ***	0.0463	0.0474 ***	0.0416 ***
	(0.0294)	(0.0104)	(0.0139)	(0.0310)	(0.0125)	(0.0098)
TFP growth(-2)	0.0250	0.0255	0.0275	0.0030	0.0041	0.0029
	(0.0294)	(0.0337)	(0.0302)	(0.0272)	(0.0324)	(0.0280)
TFP growth(-3)				0.0778	0.0786	0.0589
				(0.0622)	(0.0513)	(0.0448)
TFP growth(-4)				0.0040	0.0056	0.0119
				(0.0686)	(0.0683)	(0.0662)
First round VC/R&D(-1)	0.1465 *	0.1372 ***	0.1462 ***	0.1410	0.1365 ***	0.1465 ***
	(0.0882)	(0.0478)	(0.0546)	(0.0911)	(0.0460)	(0.0485)
First round VC/R&D(-2)	0.0915	0.0829 ***	0.0835 ***	0.0902	0.0868 ***	0.0801 **
	(0.0597)	(0.0189)	(0.0277)	(0.0617)	(0.0205)	(0.0339)
First round VC/R&D(-3)				-0.0266	-0.0321	-0.0325
				(0.0877)	(0.0465)	(0.0340)
First round VC/R&D(-4)				-0.0329	-0.0386	0.0731
				(0.1070)	(0.1281)	(0.1606)
Arellano-Bond AR(1) Test: p-value		0.11	0.11		0.11	0.11
Arellano-Bond AR(2) Test: p-value		0.21	0.22		0.16	0.14
Sargan Test: p-value		0.00	0.00		0.01	0.01
Granger-Causality Test:						
Wald Statistic	3.75	18.42	11.30	10.69	60.19	58.63
p-value	(0.15)	(0.00)	(0.00)	(0.03)	(0.00)	(0.00)

Dependent Variable = Follow-on round VC/R&D

	Lag = 2			Lag = 4		
Independent Variable	**LSDV**	**D-GMM**	**S-GMM**	**LSDV**	**D-GMM**	**S-GMM**
TFP growth(-1)	0.0941	0.0950	0.1468 **	0.0887	0.0900	0.1052 *
	(0.0680)	(0.0642)	(0.0649)	(0.0622)	(0.0564)	(0.0548)
TFP growth(-2)	-0.0303	-0.0281	0.0209	-0.0569	-0.0553	-0.0271
	(0.0446)	(0.0426)	(0.0459)	(0.0450)	(0.0466)	(0.0467)
TFP growth(-3)				0.0623	0.0632 ***	0.0261
				(0.0584)	(0.0167)	(0.0205)
TFP growth(-4)				0.1412 **	0.1428 **	0.2103 ***
				(0.0708)	(0.0660)	(0.0661)
Follow-on round VC/R&D(-1)	0.6124 ***	0.6080 ***	0.6129 ***	0.5965 ***	0.5942 ***	0.5871 ***
	(0.1931)	(0.1416)	(0.1393)	(0.1895)	(0.1368)	(0.1351)
Follow-on round VC/R&D(-2)	0.0805	0.0707	0.0567	0.0610	0.0586	0.0250
	(0.1517)	(0.1642)	(0.1493)	(0.1471)	(0.1556)	(0.1590)
Follow-on round VC/R&D(-3)				0.0219	0.0179	0.0472
				(0.0673)	(0.0637)	(0.0499)
Follow-on round VC/R&D(-4)				0.0364	0.0326	0.0198
				(0.0655)	(0.0622)	(0.0711)
Arellano-Bond AR(1) Test: p-value		0.03	0.03		0.03	0.03
Arellano-Bond AR(2) Test: p-value		0.23	0.30		0.53	0.97
Sargan Test: p-value		0.00	0.00		0.00	0.00
Granger-Causality Test:						
Wald Statistic	2.17	4.75	5.77	8.62	17.92	56.67
p-value	(0.34)	(0.09)	(0.06)	(0.07)	(0.00)	(0.00)

Table 5-A: Testing VC-First Hypothesis on TFP growth for Selected Industries

Sample period is 1972-2001. "First Round" refers to venture capital investments made in companies that have never received venture capital financing before. "Follow-on Round" refers to venture capital investments made in companies that have received venture capital financing before. "R&D" refers to privately funded R&D expenditure. For each industry, the first and second columns display OLS results of the regression with up to a quadratic time trend and the one with the time trend and a control variable (i.e. CapUtil (top) and ERISA (bottom)), respectively, other than lagged venture capital investments and TFP growth. Constant terms and coefficients on autoregressive terms are not reported. Estimates with *, **, and *** are significant at 10%, 5%, and 1% level. Heteroskedasticity robust standard errors are in parentheses. The null hypothesis for Granger-causality test is that all coefficients on venture capital investments (top) and TFP growth (bottom) are zero.

Dependent Variable = TFP growth

Independent Variable	Drugs		Office and Computing Machines		Communication and Electronic		Other Electrical Equipment		Professional and Scientific Instruments	
First VC/R&D(-1)	1.7088 *	1.6607	-1.2897	-0.2544	-2.5342 **	-2.5672 **	-0.7350 ***	-0.2101	-0.1065	0.0853
	(0.8734)	(1.0728)	(0.8611)	(0.7290)	(1.1012)	(1.1533)	(0.1828)	(0.1856)	(0.5757)	(0.4475)
First VC/R&D(-2)	0.4553	0.4245	0.9568	0.5649	0.0055	-0.1404	0.1821	-0.0046	-0.8805	-0.6088
	(1.1008)	(1.2297)	(1.7009)	(1.6123)	(1.7279)	(1.8964)	(0.4873)	(0.3360)	(0.6161)	(0.5478)
First VC/R&D(-3)	-0.5559	-0.5727	-0.6018	-1.3572	0.5448	0.4702	-0.3743	-0.3446	0.6445	0.3074
	(0.9679)	(1.0154)	(1.6016)	(1.5633)	(1.8275)	(1.9389)	(0.4162)	(0.2582)	(0.6823)	(0.6251)
First VC/R&D(-4)	0.6989	0.6763	0.3671	1.6479	-3.2737	-2.7254	0.2648	-0.0618	0.2621	0.6477
	(1.0737)	(1.1308)	(1.5501)	(1.5158)	(2.1122)	(2.8698)	(0.3208)	(0.2720)	(0.5983)	(0.6933)
Trend	-1.2305 ***	-1.2284 ***	-1.3008	0.0461	-1.1952 **	-1.3854 *	-0.2045	0.1667	-0.4515 **	-0.5038 ***
	(0.3830)	(0.4010)	(0.9970)	(0.8415)	(0.4883)	(0.7178)	(0.2610)	(0.1526)	(0.2036)	(0.1767)
$Trend^2$	0.0205 **	0.0207 **	0.0339	-0.0033	0.0496 ***	0.0546 ***	0.0057	-0.0051	0.0078	0.0084 *
	(0.0080)	(0.0085)	(0.0249)	(0.0210)	(0.0164)	(0.0209)	(0.0061)	(0.0040)	(0.0053)	(0.0045)
CapUtil		-0.0139		0.7900 ***		0.1095		0.3359 ***		0.1938 **
		(0.1164)		(0.1848)		(0.2530)		(0.0580)		(0.0813)
Granger-Causality Test:										
Wald Statistic	6.31	3.77	5.38	1.34	20.55	20.17	24.00	5.82	4.54	3.92
p-value	(0.18)	(0.44)	(0.25)	(0.86)	(0.00)	(0.00)	(0.00)	(0.21)	(0.34)	(0.42)

Dependent Variable = TFP growth

Independent Variable	Drugs		Office and Computing Machines		Communication and Electronic		Other Electrical Equipment		Professional and Scientific Instruments	
Follow-on VC/R&D(-1)	0.2137	0.1375	-0.3791 *	-0.1445	-1.6971 **	-1.8121 **	-0.1019	0.0659	-0.1481	0.0258
	(0.3010)	(0.3037)	(0.2120)	(0.2408)	(0.7363)	(0.7680)	(0.1785)	(0.1402)	(0.1583)	(0.1579)
Follow-on VC/R&D(-2)	0.7907	0.8340	0.3577	0.3034	0.7491	1.0818	-0.3327	-0.2917	-0.0204	0.0076
	(0.5331)	(0.5226)	(0.3868)	(0.4097)	(1.3189)	(1.4884)	(0.8208)	(0.6073)	(0.3018)	(0.2737)
Follow-on VC/R&D(-3)	-0.1511	-0.1400	-0.1032	-0.2007	-0.4883	-0.7854	-0.2768	-0.4746	0.3445	0.1995
	(0.8167)	(0.8320)	(0.4325)	(0.5908)	(1.4030)	(1.5861)	(0.6034)	(0.3753)	(0.2697)	(0.2395)
Follow-on VC/R&D(-4)	0.7686	0.8365	-0.2621	0.1647	-1.7090	-1.3677	0.6095	0.1842	0.0020	0.1498
	(0.6308)	(0.6598)	(0.7275)	(0.7911)	(1.6605)	(1.8995)	(0.7728)	(0.5649)	(0.2337)	(0.1800)
Trend	-1.4460 ***	-1.4476 ***	-0.8658	-0.1004	-0.6657	-0.9791 *	-0.2642	0.2758	-0.5504 ***	-0.5628 ***
	(0.3107)	(0.3400)	(1.1364)	(1.0082)	(0.4429)	(0.5340)	(0.2433)	(0.1744)	(0.1750)	(0.1767)
$Trend^2$	0.0189 **	0.0191 **	0.0241	0.0008	0.0587 ***	0.0651 ***	0.0064	-0.0078 *	0.0090 *	0.0073 *
	(0.0081)	(0.0086)	(0.0280)	(0.0257)	(0.0187)	(0.0181)	(0.0052)	(0.0041)	(0.0048)	(0.0043)
CapUtil		-0.0727		0.7330 ***		0.1685		0.3570 ***		0.2206 **
		(0.0845)		(0.2334)		(0.1858)		(0.0669)		(0.0876)
Granger-Causality Test:										
Wald Statistic	14.42	12.33	8.01	0.79	27.10	31.20	51.46	2.46	3.98	5.86
p-value	(0.01)	(0.02)	(0.09)	(0.94)	(0.00)	(0.00)	(0.00)	(0.65)	(0.41)	(0.21)

Table 5-B: Testing Innovation-First Hypothesis on TFP growth for Selected Industries

Sample period is 1972-2001. "First Round" refers to venture capital investments made in companies that have never received venture capital financing before. "Follow-on Round" refers to venture capital investments made in companies that have received venture capital financing before. "R&D" refers to privately funded R&D expenditure. For each industry, the first and second columns display OLS results of the regression with up to a quadratic time trend and the one with the time trend and a control variable (i.e. CapUtil (top) and ERISA (bottom)), respectively, other than lagged venture capital investments and TFP growth. Constant terms and coefficients on autoregressive terms are not reported. Estimates with *, **, and *** are significant at 10%, 5%, and 1% level. Heteroskedasticity robust standard errors are in parentheses. The null hypothesis for Granger-causality test is that all coefficients on venture capital investments (top) and TFP growth (bottom) are zero

Dependent Variable = First round VC/R&D

Independent Variable	Drugs		Office and Computing Machines		Communication and Electronic		Other Electrical Equipment		Professional and Scientific Instruments	
TFP growth(-1)	0.0062	0.0257	0.0301	0.0343	0.1017 *	0.0833	-0.0927	-0.0994	0.0268	0.0348
	(0.0419)	(0.0479)	(0.0449)	(0.0457)	(0.0608)	(0.0585)	(0.1624)	(0.1713)	(0.1135)	(0.1143)
TFP growth(-2)	0.0160	0.0642 *	0.0276	0.0335	-0.1057	-0.0876	0.0475	0.0428	-0.0635	-0.0632
	(0.0346)	(0.0356)	(0.0390)	(0.0343)	(0.0730)	(0.0705)	(0.1106)	(0.1128)	(0.0767)	(0.0800)
TFP growth(-3)	0.0059	0.0329	0.0537	0.0443	-0.0348	-0.0769 *	-0.0281	-0.0228	-0.0203	-0.0200
	(0.0457)	(0.0500)	(0.0512)	(0.0401)	(0.0464)	(0.0415)	(0.0828)	(0.0881)	(0.0790)	(0.0780)
TFP growth(-4)	-0.0198	0.0075	0.0633	0.0615	0.1910 ***	0.1865 ***	-0.1635	-0.1716	-0.0246	-0.0243
	(0.0545)	(0.0460)	(0.0449)	(0.0424)	(0.0609)	(0.0589)	(0.1972)	(0.2031)	(0.0792)	(0.0800)
Trend	-0.0823	-0.2448 *	-0.4544 *	-0.9163 ***	0.0423	-0.3887	-0.0848	-0.0297	-0.0361	-0.0747
	(0.0673)	(0.1266)	(0.2502)	(0.3358)	(0.1053)	(0.2441)	(0.2215)	(0.2904)	(0.1075)	(0.2075)
Trend^2	0.0037 **	0.0082 **	0.0137 *	0.0234 ***	-0.0007	0.0094	0.0050	0.0039	0.0021	0.0029
	(0.0018)	(0.0034)	(0.0071)	(0.0084)	(0.0035)	(0.0062)	(0.0067)	(0.0077)	(0.0026)	(0.0047)
ERISA		1.1826		2.6334 **		2.0027 **		-0.3320		0.2497
		(0.7890)		(1.2852)		(0.9144)		(1.0297)		(0.8029)
Granger-Causality Test:										
Wald Statistic	0.47	3.70	7.46	8.74	23.50	19.51	1.86	1.63	1.07	1.16
p-value	(0.98)	(0.45)	(0.11)	(0.07)	(0.00)	(0.00)	(0.76)	(0.80)	(0.90)	(0.89)

Dependent Variable = Follow-on round VC/R&D

Independent Variable	Drugs		Office and Computing Machines		Communication and Electronic		Other Electrical Equipment		Professional and Scientific Instruments	
TFP growth(-1)	0.0532	0.1306	0.0903	0.1072	-0.0757	-0.0985	-0.6629	-0.6510	0.0446	0.0843
	(0.1436)	(0.1834)	(0.1857)	(0.1927)	(0.0994)	(0.1053)	(0.5189)	(0.5344)	(0.2115)	(0.2264)
TFP growth(-2)	0.0229	0.1616	-0.0757	-0.0638	-0.0099	-0.0017	-0.2497	-0.2390	-0.1281	-0.1312
	(0.1247)	(0.1693)	(0.1515)	(0.1482)	(0.1343)	(0.1381)	(0.3178)	(0.3379)	(0.1513)	(0.1585)
TFP growth(-3)	0.1806	0.2727	0.0776	0.0467	-0.1708	-0.2240 *	-0.2243	-0.2415	-0.2233	-0.2201
	(0.1749)	(0.2067)	(0.1957)	(0.1917)	(0.1225)	(0.1194)	(0.2803)	(0.2831)	(0.1648)	(0.1699)
TFP growth(-4)	-0.1343	-0.0224	0.3417	0.3377	0.4526 ***	0.4492 ***	-0.6836	-0.6635	0.1185	0.1175
	(0.1260)	(0.1399)	(0.2267)	(0.2065)	(0.1372)	(0.1289)	(0.5586)	(0.5793)	(0.1553)	(0.1594)
Trend	-0.3022	-0.6190	-0.9695	-2.1114	0.2243	-0.3126	-0.8449	-0.9932	-0.1684	-0.3581
	(0.2471)	(0.3795)	(1.0936)	(1.4193)	(0.1738)	(0.3550)	(0.6657)	(0.7891)	(0.1997)	(0.3518)
Trend^2	0.0098 *	0.0195 *	0.0309	0.0548	-0.0031	0.0094	0.0315	0.0343	0.0104 *	0.0142 *
	(0.0052)	(0.0106)	(0.0307)	(0.0367)	(0.0066)	(0.0100)	(0.0209)	(0.0223)	(0.0060)	(0.0083)
ERISA		2.7497		6.1451		2.7059		0.8235		1.0863
		(2.3223)		(4.5897)		(1.7798)		(2.6258)		(1.0429)
Granger-Causality Test:										
Wald Statistic	2.21	2.40	3.52	3.82	24.75	32.18	1.75	1.64	4.45	4.27
p-value	(0.70)	(0.66)	(0.47)	(0.43)	(0.00)	(0.00)	(0.78)	(0.80)	(0.35)	(0.37)

Table 6-A: Testing for VC-first Hypothesis on Patent

Does venture capital investment cause innovation? Dependent variables are ln(Patent), which is logarithm of annual patent applications that were eventually granted. Independent variables are lagged terms of various measures of venture capital investments and lagged (logarithms of) patent counts. Sample period is 1970-2001 (2 lags) or 1972-2001 (4 lags). "First Round" refers to venture capital investments made in companies that have never received venture capital financing before. "Follow-on Round" refers to venture capital investments made in companies that have received venture capital financing before. "R&D" refers to privately funded R&D expenditure. Estimation results from least squares dummy variable (LSDV), one-step difference GMM (D-GMM), and one-step system GMM (S-GMM) estimation are presented. Coefficients on time dummies are not reported. Estimates with *, **, and *** are significant at 10%, 5%, and 1% level. Heteroskedasticity robust standard errors are in parentheses. The null hypothesis for Granger-causality test is that all coefficients on venture capital investments are zero.

Dependent Variable = ln(Patent)

	Lag = 2			Lag = 4		
Independent Variable	**LSDV**	**D-GMM**	**S-GMM**	**LSDV**	**D-GMM**	**S-GMM**
First round VC/R&D(-1)	0.0002	0.0001	0.0003	0.0001	0.0000	0.0003
	(0.0011)	(0.0015)	(0.0013)	(0.0012)	(0.0015)	(0.0014)
First round VC/R&D(-2)	-0.0005	-0.0005	-0.0005	-0.0004	-0.0004	-0.0004
	(0.0013)	(0.0014)	(0.0012)	(0.0014)	(0.0012)	(0.0012)
First round VC/R&D(-3)				-0.0004	-0.0005	0.0001
				(0.0015)	(0.0010)	(0.0012)
First round VC/R&D(-4)				-0.0015	-0.0016	-0.0018
				(0.0016)	(0.0020)	(0.0020)
ln(Patent)(-1)	0.9068 ***	0.9037 ***	0.9603 ***	0.9126 ***	0.9116 ***	0.9598 ***
	(0.0900)	(0.0940)	(0.0953)	(0.0983)	(0.0952)	(0.0983)
ln(Patent)(-2)	0.0687	0.0706	0.0321	0.1452 **	0.1450 ***	0.0598
	(0.0825)	(0.0882)	(0.0956)	(0.0734)	(0.0404)	(0.0432)
ln(Patent)(-3)				-0.0492	-0.0487	0.0006
				(0.0754)	(0.0537)	(0.0519)
ln(Patent)(-4)				-0.0481	-0.0469	-0.0295
				(0.0519)	(0.0630)	(0.0623)
Arellano-Bond AR(1) Test: p-value		0.00	0.00		0.00	0.00
Arellano-Bond AR(2) Test: p-value		0.17	0.10		0.06	0.01
Sargan Test: p-value		0.00	0.00		0.02	0.00
Granger-Causality Test:						
Wald Statistic	0.16	0.17	0.21	1.01	0.96	1.08
p-value	(0.93)	(0.92)	(0.90)	(0.91)	(0.92)	(0.90)

Dependent Variable = ln(Patent)

	Lag = 2			Lag = 4		
Independent Variable	**LSDV**	**D-GMM**	**S-GMM**	**LSDV**	**D-GMM**	**S-GMM**
Follow-on round VC/R&D(-1)	-0.0066 ***	-0.0044 **	-0.0039 *	-0.0041 **	-0.0042 **	-0.0039 **
	(0.0024)	(0.0022)	(0.0020)	(0.0017)	(0.0019)	(0.0017)
Follow-on round VC/R&D(-2)	0.0052 ***	0.0014	0.0013 *	0.0006	0.0006	0.0002
	(0.0020)	(0.0010)	(0.0007)	(0.0015)	(0.0007)	(0.0006)
Follow-on round VC/R&D(-3)				0.0002	0.0001	0.0008
				(0.0011)	(0.0011)	(0.0015)
Follow-on round VC/R&D(-4)				0.0032 ***	0.0032 ***	0.0036 ***
				(0.0012)	(0.0009)	(0.0012)
ln(Patent)(-1)	0.9684 ***	0.8764 ***	0.9371 ***	0.8814 ***	0.8811 ***	0.9260 ***
	(0.0910)	(0.0721)	(0.0771)	(0.0950)	(0.0745)	(0.0752)
ln(Patent)(-2)	0.0445	0.1182 **	0.0673	0.1671 **	0.1670 ***	0.1015 ***
	(0.0865)	(0.0523)	(0.0699)	(0.0692)	(0.0381)	(0.0378)
ln(Patent)(-3)				-0.0281	-0.0280	0.0221
				(0.0735)	(0.0421)	(0.0458)
ln(Patent)(-4)				-0.0393	-0.0389	-0.0501
				(0.0466)	(0.0607)	(0.0637)
Arellano-Bond AR(1) Test: p-value		0.00	0.00		0.00	0.00
Arellano-Bond AR(2) Test: p-value		0.17	0.08		0.17	0.01
Sargan Test: p-value		0.01	0.00		0.02	0.00
Granger-Causality Test:						
Wald Statistic	9.02	4.48	5.03	12.83	17.61	18.52
p-value	(0.01)	(0.11)	(0.08)	(0.01)	(0.00)	(0.00)

Table 6-B: Testing for Innovation-first Hypothesis on Patent

Does innovation cause venture capital investment? Dependent variables are various measures of venture capital investments. Independent variables are lagged (logarithms of) patent applications that were eventually granted and lagged terms of various measures of venture capital investments. Sample period is 1970-2001 (2 lags) or 1972-2001 (4 lags). "First Round" refers to venture capital investments made in companies that have never received venture capital financing before. "Follow-on Round" refers to venture capital investments made in companies that have received venture capital financing before. "R&D" refers to privately funded R&D expenditure. Estimation results from least squares dummy variable (LSDV), one-step difference GMM (D-GMM), and one-step system GMM (S-GMM) estimation are presented. Coefficients on time dummies are not reported. Estimates with *, **, and *** are significant at 10%, 5%, and 1% level. Heteroskedasticity robust standard errors are in parentheses. The null hypothesis for Granger-causality test is that all coefficients on (logarithms of) patent counts are zero.

Dependent Variable = First round VC/R&D

	Lag = 2			Lag = 4		
Independent Variable	**LSDV**	**D-GMM**	**S-GMM**	**LSDV**	**D-GMM**	**S-GMM**
ln(Patent)(-1)	1.4184	1.3218	1.5569	1.4261	1.3303	1.4962
	(1.6753)	(1.5151)	(1.5381)	(1.8734)	(1.7526)	(1.5857)
ln(Patent)(-2)	-1.1110	-1.0725	-1.5337	-0.1537	-0.1217	0.3038
	(2.7281)	(2.7586)	(1.9979)	(1.5240)	(1.3451)	(1.2771)
ln(Patent)(-3)				-1.3392	-1.2939	0.4005
				(2.1991)	(1.5819)	(1.1720)
ln(Patent)(-4)				0.3483	0.3165	-2.2978
				(1.9480)	(1.8473)	(2.0974)
First round VC/R&D(-1)	0.1535 *	0.1439 ***	0.1581 ***	0.1487 *	0.1442 ***	0.1566 **
	(0.0880)	(0.0476)	(0.0601)	(0.0880)	(0.0508)	(0.0628)
First round VC/R&D(-2)	0.0941 *	0.0852 ***	0.0873 **	0.0968 *	0.0939 ***	0.0851 *
	(0.0561)	(0.0237)	(0.0345)	(0.0575)	(0.0255)	(0.0443)
First round VC/R&D(-3)				-0.0285	-0.0389	-0.0363
				(0.0877)	(0.0381)	(0.0361)
First round VC/R&D(-4)				-0.0326	-0.0438	0.0739
				(0.1051)	(0.1271)	(0.1672)
Arellano-Bond AR(1) Test: p-value		0.12	0.10		0.12	0.10
Arellano-Bond AR(2) Test: p-value		0.22	0.20		0.26	0.15
Sargan Test: p-value		0.00	0.00		0.01	0.00
Granger-Causality Test:						
Wald Statistic	2.77	3.83	2.66	3.39	9.40	7.01
p-value	(0.25)	(0.15)	(0.26)	(0.49)	(0.05)	(0.14)

Dependent Variable = Follow-on round VC/R&D

	Lag = 2			Lag = 4		
Independent Variable	**LSDV**	**D-GMM**	**S-GMM**	**LSDV**	**D-GMM**	**S-GMM**
ln(Patent)(-1)	1.7858	1.7733	2.2382 *	1.6728	1.6433	2.1024 *
	(1.6217)	(1.2473)	(1.1783)	(1.7325)	(1.5636)	(1.1969)
ln(Patent)(-2)	1.7671	1.8791	-0.5228	1.7092	1.7102	2.8331
	(2.0985)	(2.3399)	(1.2930)	(2.2427)	(1.5458)	(1.8379)
ln(Patent)(-3)				-0.3670	-0.3572	0.5022
				(2.4596)	(2.6914)	(2.9893)
ln(Patent)(-4)				0.8117	0.8377	-4.0234
				(2.2774)	(1.9030)	(3.1017)
Follow-on round VC/R&D(-1)	0.5438 ***	0.5394 ***	0.5957 ***	0.5383 ***	0.5373 ***	0.5885 ***
	(0.1792)	(0.1201)	(0.1342)	(0.1792)	(0.1207)	(0.1382)
Follow-on round VC/R&D(-2)	0.0636	0.0571	0.0636	0.0522	0.0508	0.0522
	(0.1436)	(0.1553)	(0.1375)	(0.1451)	(0.1551)	(0.1544)
Follow-on round VC/R&D(-3)				0.0107	0.0084	0.0753
				(0.0652)	(0.0560)	(0.0475)
Follow-on round VC/R&D(-4)				0.0017	-0.0005	-0.0183
				(0.0586)	(0.0478)	(0.0836)
Arellano-Bond AR(1) Test: p-value		0.03	0.03		0.03	0.03
Arellano-Bond AR(2) Test: p-value		0.24	0.41		0.47	0.86
Sargan Test: p-value		0.00	0.00		0.00	0.00
Granger-Causality Test:						
Wald Statistic	7.53	17.65	8.73	8.81	20.38	12.94
p-value	(0.02)	(0.00)	(0.01)	(0.07)	(0.00)	(0.01)

Table 7-A: Testing for VC-first Hypothesis on Patent for Selected Industries

Sample period is 1972-2001. "First Round" refers to venture capital investments made in companies that have never received venture capital financing before. "Follow-on Round" refers to venture capital investments made in companies that have received venture capital financing before. "R&D" refers to privately funded R&D expenditure. For each industry, the first and second columns display OLS results of the regression with up to a quadratic time trend and the one with the time trend and a control variable (i.e. D1981 (top) and ERISA (bottom)), respectively, other than lagged venture capital investments and patent counts. Constant terms and coefficients on autoregressive terms are not reported. Estimates with *, **, and *** are significant at 10%, 5%, and 1% level. Heteroskedasticity robust standard errors are in parentheses. The null hypothesis for Granger-causality test is that all coefficients on venture capital investments (top) and (logarithms of) patent counts (bottom) are zero.

Dependent Variable = ln(Patent)

Independent Variable	Drugs		Office and Computing Machines		Communication and Electronic		Other Electrical Equipment		Professional and Scientific Instruments	
First VC/R&D(-1)	-0.0461	-0.0477	-0.0301 ***	-0.0308 **	-0.0463 ***	-0.0479 ***	-0.0286 ***	-0.0295 ***	-0.0468 **	-0.0462 *
	(0.0527)	(0.0559)	(0.0109)	(0.0123)	(0.0113)	(0.0104)	(0.0032)	(0.0032)	(0.0229)	(0.0240)
First VC/R&D(-2)	-0.0264	-0.0283	0.0067	0.0069	-0.0046	-0.0082	0.0086	0.0063	0.0110	0.0102
	(0.0623)	(0.0677)	(0.0162)	(0.0167)	(0.0166)	(0.0189)	(0.0079)	(0.0073)	(0.0257)	(0.0274)
First VC/R&D(-3)	-0.0098	-0.0125	-0.0140	-0.0148	0.0073	0.0055	-0.0143 **	-0.0142 **	-0.0418 **	-0.0396 **
	(0.0803)	(0.0868)	(0.0177)	(0.0184)	(0.0154)	(0.0155)	(0.0071)	(0.0065)	(0.0162)	(0.0166)
First VC/R&D(-4)	-0.1927 *	-0.1945 *	0.0070	0.0067	-0.0216	-0.0201	0.0146 ***	0.0112 **	-0.0160	-0.0167
	(0.1107)	(0.1139)	(0.0174)	(0.0184)	(0.0142)	(0.0144)	(0.0048)	(0.0054)	(0.0266)	(0.0263)
Trend	0.0146	0.0118	-0.0221	-0.0234	-0.1194 ***	-0.1231 ***	-0.0305 *	-0.0329 **	-0.0266	-0.0257
	(0.0163)	(0.0214)	(0.0258)	(0.0289)	(0.0317)	(0.0317)	(0.0174)	(0.0138)	(0.0208)	(0.0213)
Trend^2	0.0012	0.0013	0.0013	0.0013	0.0048 ***	0.0049 ***	0.0011 **	0.0014 ***	0.0017 *	0.0017 *
	(0.0012)	(0.0012)	(0.0011)	(0.0012)	(0.0012)	(0.0012)	(0.0005)	(0.0004)	(0.0009)	(0.0009)
D1981		0.0172		0.0134		0.0319		-0.0851 ***		-0.0164
		(0.1354)		(0.0780)		(0.0448)		(0.0315)		(0.0476)
Granger-Causality Test:										
Wald Statistic	3.89	3.52	21.18	18.07	29.26	34.96	95.17	101.73	13.07	11.01
p-value	(0.42)	(0.47)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.03)

Dependent Variable = ln(Patent)

Independent Variable	Drugs		Office and Computing Machines		Communication and Electronic		Other Electrical Equipment		Professional and Scientific Instruments	
Follow-on VC/R&D(-1)	-0.0730 ***	-0.0739 ***	-0.0095 ***	-0.0094 **	-0.0156 ***	-0.0153 ***	-0.0043	-0.0065	-0.0221 ***	-0.0242 ***
	(0.0158)	(0.0163)	(0.0033)	(0.0037)	(0.0032)	(0.0032)	(0.0053)	(0.0051)	(0.0076)	(0.0072)
Follow-on VC/R&D(-2)	0.0404 *	0.0412 *	-0.0033	-0.0033	-0.0117 *	-0.0117 *	-0.0217	-0.0171	0.0056	0.0045
	(0.0236)	(0.0235)	(0.0053)	(0.0055)	(0.0062)	(0.0064)	(0.0208)	(0.0204)	(0.0155)	(0.0146)
Follow-on VC/R&D(-3)	-0.0138	-0.0121	0.0059	0.0061	0.0253 **	0.0254 **	0.0104	0.0108	0.0020	0.0011
	(0.0291)	(0.0299)	(0.0050)	(0.0059)	(0.0121)	(0.0122)	(0.0172)	(0.0164)	(0.0160)	(0.0142)
Follow-on VC/R&D(-4)	-0.1450 ***	-0.1421 **	-0.0079	-0.0080	-0.0193	-0.0198	0.0121	0.0064	0.0054	0.0057
	(0.0558)	(0.0565)	(0.0072)	(0.0074)	(0.0120)	(0.0125)	(0.0190)	(0.0167)	(0.0115)	(0.0114)
Trend	-0.0190	-0.0089	-0.0700 **	-0.0687 *	-0.1102 ***	-0.1115 ***	-0.0328 *	-0.0370 **	-0.0269	-0.0329
	(0.0151)	(0.0180)	(0.0310)	(0.0354)	(0.0346)	(0.0355)	(0.0175)	(0.0145)	(0.0216)	(0.0208)
Trend^2	0.0054 ***	0.0053 ***	0.0035 **	0.0035 **	0.0047 ***	0.0048 ***	0.0012 **	0.0016 ***	0.0015 *	0.0020 **
	(0.0013)	(0.0013)	(0.0014)	(0.0015)	(0.0012)	(0.0013)	(0.0005)	(0.0005)	(0.0009)	(0.0009)
D1981		-0.0755		-0.0078		-0.0131		-0.0964 **		-0.0862 **
		(0.0946)		(0.0675)		(0.0366)		(0.0377)		(0.0362)
Granger-Causality Test:										
Wald Statistic	34.18	31.44	27.80	24.79	67.35	66.01	38.92	49.20	14.44	18.43
p-value	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)

Table 7-B: Testing for Innovation-First Hypothesis on Patent for Selected Industries

Sample period is 1972-2001. "First Round" refers to venture capital investments made in companies that have never received venture capital financing before. "Follow-on Round" refers to venture capital investments made in companies that have received venture capital financing before. "R&D" refers to privately funded R&D expenditure. For each industry, the first and second columns display OLS results of the regression with up to a quadratic time trend and the one with the time trend and a control variable (i.e. D1981 (top) and ERISA (bottom)), respectively, other than lagged venture capital investments and patent counts. Constant terms and coefficients on autoregressive terms are not reported. Estimates with *, **, and *** are significant at 10%, 5%, and 1% level. Heteroskedasticity robust standard errors are in parentheses. The null hypothesis for Granger-causality test is that all coefficients on venture capital investments (top) and (logarithms of) patent counts (bottom) are zero

Dependent Variable = First round VC/R&D

Independent Variable	**Drugs**		**Office and Computing Machines**		**Communication and Electronic**		**Other Electrical Equipment**		**Professional and Scientific Instruments**	
ln(Patent)(-1)	-1.2679 *	-1.2238 *	1.1573	0.9166	-5.1298	-7.5302	-13.1245	-13.5998	-5.4855 *	-5.7242
	(0.7126)	(0.6704)	(5.2803)	(5.0493)	(8.9284)	(8.3459)	(10.3067)	(10.8085)	(3.2876)	(3.6471)
ln(Patent)(-2)	0.0345	0.0557	-0.2414	-0.4979	8.0505	7.2705	12.8759	13.3490	-2.5881	-2.5143
	(0.4871)	(0.4987)	(8.9768)	(8.4587)	(7.2538)	(5.9559)	(8.6352)	(9.1377)	(1.9301)	(2.0389)
ln(Patent)(-3)	-0.8294	-0.8600	13.4245	11.5135	17.3130	16.2333	1.9953	1.8962	4.3827	4.6211
	(0.7723)	(0.7508)	(9.4009)	(9.6610)	(13.6285)	(12.5084)	(14.0747)	(14.3841)	(3.5673)	(3.8565)
ln(Patent)(-4)	-0.3379	-0.5090	-0.7059	1.4448	-4.2130	-1.0507	-10.1563	-10.0571	-3.2873	-3.4261
	(0.7877)	(0.7855)	(4.8305)	(4.7773)	(6.5011)	(5.5893)	(10.2661)	(10.5107)	(2.5342)	(2.6345)
Trend	-0.1317 *	-0.2698 *	1.7186 **	1.2290 *	1.5874	0.8825	-0.6495	-0.5941	-0.3932	-0.3526
	(0.0701)	(0.1475)	(0.6933)	(0.7066)	(1.0063)	(0.9158)	(0.4678)	(0.4938)	(0.2654)	(0.3008)
Trend^2	0.0100 **	0.0135 **	-0.0664 **	-0.0546 **	-0.0563	-0.0379	0.0249	0.0239	0.0206 *	0.0198
	(0.0043)	(0.0054)	(0.0275)	(0.0262)	(0.0385)	(0.0342)	(0.0166)	(0.0170)	(0.0116)	(0.0121)
ERISA		0.7533		2.4415		3.1386 **		-0.2961		-0.2454
		(0.7414)		(1.6600)		(1.5063)		(0.5995)		(0.8026)
Granger-Causality Test:										
Wald Statistic	6.11	6.64	9.44	11.66	6.44	17.89	4.33	4.27	6.45	6.11
p-value	(0.19)	(0.16)	(0.05)	(0.02)	(0.17)	(0.00)	(0.36)	(0.37)	(0.17)	(0.19)

Dependent Variable = Follow-on round VC/R&D

Independent Variable	**Drugs**		**Office and Computing Machines**		**Communication and Electronic**		**Other Electrical Equipment**		**Professional and Scientific Instruments**	
ln(Patent)(-1)	-2.2681	-2.1595	0.6912	-0.2671	1.5272	2.0936	-58.6360	-58.3796	-19.5063 **	-19.9613 **
	(2.6882)	(2.5644)	(21.3191)	(20.8175)	(13.1803)	(13.7480)	(38.9337)	(40.2748)	(7.9847)	(8.4396)
ln(Patent)(-2)	0.4537	0.5860	-2.3284	-3.2573	32.0341	33.7924	41.1320	40.8590	0.8176	0.7787
	(2.4918)	(2.4461)	(30.1300)	(28.2122)	(24.8393)	(24.0092)	(36.5794)	(38.1685)	(8.7198)	(9.0246)
ln(Patent)(-3)	0.8053	0.9263	42.1723	37.5431	1.1472	2.6317	6.9828	7.0416	5.4727	5.6430
	(3.6144)	(3.6216)	(31.3159)	(32.2300)	(17.1614)	(16.2465)	(26.5569)	(27.2955)	(12.7769)	(13.2425)
ln(Patent)(-4)	-0.9592	-1.1723	0.7347	7.3479	-1.3126	2.4149	-4.3964	-4.4338	-9.4657	-9.6232
	(3.9233)	(4.0554)	(20.1682)	(20.5800)	(16.6848)	(18.1095)	(24.6770)	(25.3062)	(9.1161)	(9.4364)
Trend	-0.4232	-0.7104	5.2618 *	3.8846	3.3954	3.4326	-1.7424	-1.7794	-1.6562 **	-1.6047 **
	(0.3161)	(0.5332)	(2.9145)	(2.9803)	(2.3167)	(2.1108)	(1.4344)	(1.6270)	(0.7851)	(0.7881)
Trend^2	0.0166	0.0223	-0.2005 *	-0.1689	-0.1267	-0.1394	0.0708	0.0715	0.0763 **	0.0761 **
	(0.0196)	(0.0227)	(0.1165)	(0.1162)	(0.0907)	(0.0883)	(0.0507)	(0.0543)	(0.0325)	(0.0330)
ERISA		1.6771		7.0527		3.5492		0.2006		-0.4466
		(1.5931)		(5.4211)		(2.8914)		(2.2360)		(1.0312)
Granger-Causality Test:										
Wald Statistic	1.23	1.22	4.74	4.97	3.78	4.68	2.46	2.31	8.97	8.52
p-value	(0.87)	(0.88)	(0.31)	(0.29)	(0.44)	(0.32)	(0.65)	(0.68)	(0.06)	(0.07)