Venture Capital and Productivity*

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Abstract

Policy makers typically interpret positive relations between venture capital and innovation as an evidence that venture capital investments stimulate innovation (VC-first hypothesis). This interpretation is, however, problematic because there may be a reverse causality that innovation spurs venture capital (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 total factor productivity (TFP) growth as a measure of innovation. Evidence is mixed. Using a panel AR regression, we find that innovation significantly leads venture capital investment but not the other way around. However, if we allow for a presence of unobservable factors that influence innovation and venture capital investment simultaneously, past venture capital investments are positively and significantly related to innovation.

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1 Introduction

Policy makers who aim to stimulate economic growth often attempt to create or expand venture capital industry. 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 micro 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 investment account for patent count disproportionately relative to R&D expenditures. Using German data, Tykova (2000) also finds the positive relation between venture capital investment and patent application.[2]

A common interpretation of the results found in literature cited above is that venture capital ("VC") spurs growth and innovation of new firms. Hereafter, We call this view the *VC-first* hy-

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

[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.

pothesis. 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 industry 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 literature 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 with new firm entries. (Gans and Stern, 1998, Gilbert and Newbery, 1982, and Reinganum, 1983) Therefore, 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.

Another problem involved in interpreting the previous results as an evidence of the VC-first hypothesis is simultaneity. There may be unobservable variables and they may affect both VC

[3]The complementarity between new firms and venture capital may arise from various sources. First, a venture capitalist typically specializing 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 ,1979 and 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. Hellman 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.

investment and TFP growth. For instance, as pointed out by Kortum and Lerner, demand boom in an industry may induce more innovation affecting both R&D expenditures and more VC through formation of start-ups in the same industry. Thus, one needs to be careful about interpreting the previous results as evidence supporting the innovation-first hypothesis.

This paper addresses the causality and simultaneity issues described above by studying dynamic panel data of U.S. manufacturing industries. We use TFP growth as a measure of innovation. To address the endogeneity issue, we use panel AR regressions for both VC investments and TFP growth. The results of the analysis favor the innovation-first hypothesis but not the VC-first hypothesis. Strikingly, we cannot, at all, reject the hypothesis that VC investment does not lead TFP growth. This result is robust to alternative specification and estimation methods. To make contrast with the negative result associated with the VC-first hypothesis, we find some evidence that supports the innovation-first hypothesis; past TFP growth sometimes significantly and positively affect VC investment.

However, the VC-first hypothesis may look valid if we control for the simultaneity. To address this simultaneity issue, we assume there is an unobservable factor that affects both TFP growth and VC investment simultaneously. We also take into account the opposability that VC investment may be affect by the clarification of ERISA prudent rule and funds available for VC investment.[4] By controlling the simultaneity in this way, we find that past VC investment is positively and significantly related to TFP growth.

Besides the articles cited above, this paper is closely related to literature on financial development and growth. For instance, close to the spirit of this paper, Robinson argues (1952) how financial development follows economic development. Greenwood and Jovanovic (1990) 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 enhance economic growth. Compared to the literature that study banking sectors and stock markets, there

[4] This clarification is supposed to boost U.S. VC industries but to not affect TFP growth (Gompers and Lerner, 1998).

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 as well as motivates the use of TFP growth as a measure of innovation. The details in constructing new datasets are also discussed. Section 3 presents the results of empirical analyses. Section 4 concludes.

2 Data Description

In this section, we detail how we construct the data set for the results. There are three major difficulties in assembling this dataset. The first complication is concordance between venture capital data and TFP data. The second complication is extending TFP data over the NBER coverage. The last complication is estimation of venture capital commitment available for each industry.

2.1 Data Sources

The data analyzed in this paper come from the two sources: VentureXpert, and Bertelsman, Becker, and Gray's NBER-CES Manufacturing Industry Database ("the NBER 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. Like the NBER database, VentureXpert records SIC codes of the companies that financed from venture capitalists. However, this variable is very often missing; only 21% of the investment amount records SIC codes of the companies that received VC investment. Instead of SIC codes, VentureXpert uses its own proprietary industry classification system, the Venture Economics Industry Code ("VEIC"). There is no missing record for this VEIC variable. Reflecting industry focus of VC, some industries are classified in more detail and others are in less detail than SIC. VentureXpert reports daily VC investment data from 1960 to date. As Kortum and Lerner, we use the data only from 1965 because investment figures are mostly zero.

The NBER database draws original data from Bureau of Census and contains productivity related variables for all manufacturing industries at SIC 4-digit level.[5] The data is annual, starts from 1958 and ends in as early as 1996, which limits one from extending analysis into recent five years. Then, in order to reflect the impact of rapid increases in VC investment in the recent years in our analysis, we extend the NBER database up to 2001 in the method described in the next section. Extensive productivity data are available only in this database and it covers only manufacturing. Thus, we limit our scope to manufacturing industries. We extracted and constructed two variables from the NBER database: one is capital expenditure and the other is four-factor TFP growth.

2.2 TFP Growth as Measure of Innovation

As far as we are aware, none has used TFP growth as a measure of innovation to study how the development of VC market affects innovation. Thus, one may wonder why we use TFP growth instead of patent counts that are commonly used in the literature. The reason for use of TFP growth is that patent count is a problematic measure of innovation in assessing the role of VC investments in stimulating innovations. VC investments may encourage inventors *to patent their innovations* rather than *to innovate*. There are three justifications for this positive relation between VC investments and the patent propensity.

First, VC investments are geared towards start-up firms and these firms presumably have a high patent propensity.[6] Start-ups may use patents more often than established firms as a mean to appropriate returns to innovation. Levin et al. (1987) find that large firms generally rate patents less effective mechanisms of appropriation than the other means such as secrecy, lead time, and sales or service efforts. Nonetheless, start-ups typically do not have any of these appropriation

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

[6] For the sample of sillicon valey firms, Hellman and Puri (2000) find, venture capital backed firms are often start-ups (2 years old on average),

vehicles that established firms do because start-ups do not own their manufacturing and marketing capacities. Thus, these firms may use patents more often than established firms. Supporting this difference in patent propensity, Hall and Ham (1999), Table 2, report that design firms, specializing in product innovation in the US semiconductor industry has a higher propensity to patent than ones with manufacturing capacities.

Second, VC facilitates entries of new firms and the competitive pressure from these new firms may increase the patent propensity of established firms. These established firms often patent inferior technology for strategic reasons. (Cohen et al., 1997) As Gilbert and Newbery (1982) argue, established firms may "shelve" patent that is inferior to the most advanced technology in order to deter entry and increasing competition. This strategic motive is presumably stronger and established firms tend to patent more when the threat of competition from start-ups is strong due to supports from venture capitalists. To summarize the two arguments above, VC investment may increase the patent propensity on average through stimulating start-ups but not necessarily innovations.

Third, a change in the patent policy may affect both patent counts and VC investment. As a result, spurious correlations between patent counts and VC investment may arise. For instance, Ueda (2000) argues that enlarging the scope of patentable inventions not only increase patent counts as well as encourages inventors to ask VC for funds. Thus, VC investments and patent count may comove even though there is no change in the extent of innovations.

2.3 Concordance

One complication involved in combining VentureXpert and the NBER database is industry concordance. A single industry in the former may consist more than one industry in the latter and *vice versa*. Differences in terminology across the two distance add another difficulty. For instance, "Biotech Related Fine Chemicals" (VEIC 4311) sounds any category of "Chemicals and allied products" (SIC 2-digit, 28) and "Research, development, and testing services (except noncommercial research organizations)" (SIC 3-digit, 873). To avoid discretion in the course of this concordance and aggregation of industries, we use the industry classification scheme same as the one used by Kortum and Lerner (2001). Another benefit from using the same industry scheme as Kortum and Lerner is to make the results of this paper comparable with their results.

Kortum and Lerner aggregate 3-digit level SIC industries into 20 industries. The name of each industry and corresponding SIC codes are written in Table 1. Hereafter, we call this industry classification system "KL classification". The NBER database records both capital expenditure and TFP growth at a finer level than at KL classification. We aggregate capital expenditure by summation and TFP growth by averaging 4-digit four-factor TFP growth weighted by value added. To construct VC investment data along with KL classification, we divide data into two: data points with which SIC code is recorded and ones with which SIC code is not recorded. If a SIC code is recorded, we converted the SIC code into a KL classification code using the concordance given in Table 1. And then we assign 100% of investment amount of the record to the KL classification code into which the original SIC code was converted. If a SIC code is not recorded, VEIC is used to divide and assign KL classification codes to investment amount. The assignment rule is constructed from data records with SIC codes and thereby KL classification assigned in the way described above. For each VEIC, we obtain the distribution of investment amount over KL classification codes and use the same distribution for assigning KL classification codes to each record without SIC codes. For instance, among data points with SIC codes, total of \$202 millions are invested into Circuit Boards industry (VEIC 3140). \$60 millions are invested in Office and Computing Machine (KL classification code, 13), \$141 millions are invested in Communication and Electronic Industries (KL classification code, 15) and \$1 million is invested in Professional and Scientific Instruments Industry (KL classification code, 19). If a data point records that a company which received VC investment is in Circuit Boards Industry according to VEIC, we assign 60/202 of the investment amount to Office and Computing Machine, 141/202 of investment amount to Communication and Electronic Industries and 1/202 of investment amount to Professional and Scientific Instruments Industry.

– Table 1 Here –

Compared to the data used by Kortum and Lerner, our venture capital investment figures are significantly large. This happens because Venture Economics backfills their database. This may create 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.

2.4 Constructions of New Datasets

Before doing our empirical analyses, we construct two new datasets. Precisely, we *extend* the NBER database up to 2001 and *construct* the proxy of VC commitment ("the commitment"). The former is pursued because it is inevitable that our analysis should incorporate the impact of rapid increases in VC investment in recent years. On the other hand, the latter is used as an explanatory variable for VC investment in our extension where the simultaneity is controlled for.

2.4.1 Extension of NBER Database

Extending two series, four-factor TFP growth and capital expenditure, in the NBER database up to 2001, is pinned down to extending the following data series: value of shipments and its deflator, total real capital stock, number of employees, average number of production workers, production worker hours, annual payroll, production worker wages, cost of materials and its deflator, and total capital expenditures.[7] All the data other than the real capital stock are extracted from the latest publication of the Annual Survey of Manufacturers ("ASM") by the Bureau of Census, whereas the real capital stock alone is provided by the Federal Reserve Board. However, for every data the industry classification after 1996 is based on the North American Industry Classification System ("NAICS"). Hence, using the bridge tables as of 1997 published by the Bureau of Census, we convert the variables in ASM from NAICS-based ones to 4-digit SIC-based ones. Precisely,

[7]The deflated value of shipment is defined as the real output, and four factors are the real capital stock, production worker hours, non-production workers, and the deflated 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-based value of shipments and its deflator alone are still published by the Bureau of Economic Analysis, and thus we use them. 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 deflator for the material cost is obtained by averaging the prices using as weights each industry's uses of inputs in the Input-Output Table as of 1992 by the Bureau of Census.[8] The shipments deflators for 4-digit SIC manufacturing industries are used for manufacturing inputs. The prices for non-manufacturing inputs are obtained from corresponding producer price indices published by the Bureau of Labor Statistics. When we do not find an exact match of a non-manufacturing input with the price index, we use the index of a closely related commodity.

There are several difficulties in connecting some data series before and after 1996. First, some industries are classified as manufacturing in SIC but as non-manufacturing in NAICS. 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). Since their data are not available in the latest ASM, we use past shares to value of shipments and other data sources such as the Current Employment Statistics published by the Bureau of Labor Statistics. 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.

2.4.2 Construction of the Commitment Data

To control for the simultaneity, we employ "VC commitment data" as an instrument. Due to a high transaction cost, venture capital firms raise funds infrequently - every few to several years. And

[8] The latest Input-Output Table available when the NBER database was constructed should be the one as of 1992. This table is based on 4-digit SIC.

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 "the commitment". Here, we describe how we constructed this data.

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.[9] We call the difference between fund size and accumulated disbursement that

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

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.[10]

To construct the commitment 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, the number of funds remaining in our sample is 4787 which accounts for nearly two thirds of all such funds.[11]

Then, in the final step, we obtain the KL-classified commitment data in constant dollars by aggregating all available capitals over each KL classification in each year and deflating them. . As seen in Table 2, the commitment data fairly well captures the substantial part of actual VC investment. It can be seen that the commitment data accounts for about a half of total VC investment, although a third of VC funds are eliminated from our sample.

[10] 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.

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

– Table 2 Here –

2.5 Descriptive Statistics

Table 1 shows VC investment classified into each industry using the method described above. The table shows that VC investment in the U.S. manufacturing industry has dramatically grown during the last four decades. The amount of investment in the recent few years is more than eighty times as much as the one in 1965-69. Notably, stimulated by a sequence of regulatory changes favorable to venture capital, investment amount significantly increased from 1970s to 1980s. These changes involve clarification of ERISA prudent man rule, reduction of capital gains tax rate, and introduction of Bayh-Dole Act that facilitated technology transfer from universities to private sectors.[12] The whole VC industry experienced downturn in the early 1990s due to asset quality problems of pension funds. Those funds pull 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. VC investments are clustered. In particular, Office and Computing Machines (KL 13), Communication and electronics (KL 15), and Professional and scientific instruments (KL 19) account for two thirds of the total VC investment in manufacturing industries to date.

– Table 3 (Panel A-C) Here –

Table 3 shows the descriptive statistics of three variables examined in this paper. Panel A summarizes the annual VC investment data by industry. Comparing Panel A and Panel B, one can see that VC investment in Office and Computing Machines is not only large in absolute term but also so in relative term, being for 83.84% of capital expenditures. In other industries, the

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

relative presence of VC investments are quite small and often it is less than one percent of industry capital expenditures. Panel C summarizes annual TFP growth. Indicating positive correlation between innovation and VC investments, TFP in Office and Computing Machines industry has grown at as high as 11.8% on average. There is one caveat for interpreting this high number. One of the biggest problem to measure innovation by TFP growth is a difficulty in measuring quality improvement. Unlike cost-reducing innovation, to identify quality improvement requires detailed knowledge in assessing and measuring product quality. For this reason, TFP growth associated with quality improvement is infrequently incorporated. Computer related industries are ones that likely to incorporate this TFP growth owing to quality improvement. In 1980s, the Bureau of Census conducted the measurement of quality change in those industries with help of IBM. This is the only significant attempt made by the Bureau. For this reason, industries other than computer related ones may not exhibit substantial quality improvement in their TFP growth figure and it may be under represented.

– Figures 1 and 2 Here –

This relation between TFP growth and VC investment is shown in Figures 1 and 2. Vertical axes for these figures are all TFP growth and horizontal axis is measures of VC investment. Figures 1-A and 2-B uses the dollar amount of VC investment and Figures 1-B and 2-B uses the ratio of VC investments to capital expenditure as a measure of VC investment. Both Figures 1-A and 1-B include only first-round investments and Figure 2-A and 2-B include only follow-on investments. One difference between first-round investments and follow-on investments is found in Textile and Apparel industry. Its receipt of VC appears high in the first-round investments (Figures 1-A and 1-B) but not so in the follow-on investment (Figures 2-A and 2-B), indicating that textile and apparel firms rarely receive VC financing in more than one stage.[13]

[13] Gompers (1996) argues that staged financing should be less often for non-high tech firms because asymmetric information problems for non-high tech firms are less important than in ones high-tech firms.

3 Empirical Methods and Results

In this section, we present methods and results of empirical analyses. Underlying methods used here are panel AR regressions, studying forecasting powers of VC investments and TFP growth. We begin with examining the causality of two variables and proceed to the analysis taking account for the simultaneity issue. For all subsequent analyses, we take the sample period from 1965 to 2001.

3.1 Panel AR Regressions

We borrow the idea to examine causality problems from Granger Causality. Granger causality test examines if X causes Y by regressing X to the past realizations of X and Y and seeing if the series of Y 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 VC investment in industry i at time t. The representations of our causality test consist of estimating the following equations:

$$\begin{aligned} TFP_{i,t} &= \alpha_0 + \sum_{l=1}^{L} \beta_l VC_{i,t-l} + \sum_{l=1}^{L} \alpha_l TFP_{i,t-l} + \eta_i + \varepsilon_{i,t}, \text{ and} \quad (1) \\ VC_{i,t} &= \alpha'_0 + \sum_{l=1}^{L} \beta'_l TFP_{i,t-l} + \sum_{l=1}^{L} \alpha'_l VC_{i,t-l} + \eta'_i + \varepsilon'_{i,t}, \quad (2) \end{aligned}$$

where L is the maximum lag length, η_i and η'_i are unobserved industry-specific heterogeneities that are assumed to be *random effects*, and $\varepsilon_{i,t}$ and $\varepsilon'_{i,t}$ are idiosyncratic errors that are assumed to be mutually serially uncorrelated. No causality in Granger's sense from VC investment to TFP growth and from TFP growth to VC investment are hypothesized as $H_0 : (\beta_1, \ldots, \beta_L) = \mathbf{0}$ and $H'_0 : (\beta'_1, \ldots, \beta'_L) = \mathbf{0}$, respectively. We perform the hypothesis testing for four different VC investment variables: dollar amount and ratio to capital expenditure of first-round investment and ones 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. We estimate these two equations by the generalized least squares ("GLS") and the maximum likelihood ("ML") for the robustness of testing results.

– Table 4-A, 4-B, 5-A, and 5-B Here –

The estimation results by GLS and ML are presented in Table 4-A and B, and Table 5-A and B, respectively. Table 4-A and 5-A, and Table 4-B and 5-B report the results of estimating coefficients for the equation (1), and those of estimating coefficients for the equation (2). Standard errors in Table 4-A and 4-B are based on Eicker-White formula. For all four tables, autoregressive terms, which are presented in bottom four rows, are mostly significant, not surprisingly suggesting the presence of autocorrelation for both variables. Striking results are insignificance of VC investment coefficients and corresponding Wald statistics for regressions (a), (b), (c) and (g) in Table 4-A. Table 5-A also exhibits insignificance of likelihood ratio statistics for regressions (a), (b), (c), (e), and (g). Recall that these statistics test the null hypothesis that VC investment (in dollar amounts or in ratios to capital expenditures) does not cause TFP growth. Hence, such insignificance means that neither first-round nor follow-on round VC investment is likely to explain subsequent TFP growth significantly. In particular, the insignificance of likelihood ratio statistics for regressions (a) and (b) in Table 5-A indicates that at least VC investment in dollar amounts does not cause TFP growth. On the other hand, Wald or likelihood ratio statistics for regression (d), (f), and (h) in Table 4-A and 5-A are significant. These results may indicate that causality tests are sensitive to choices of lag length, as often reported.

On the other hand, all Wald and likelihood ratio statistics in Table 4-B and 5-B test the null hypothesis that TFP growth does not Granger-cause VC investment. In particular, all but a Wald statistics in Table 4-B and all likelihood ratio statistics in Table 5-B reject the null at 1% level. This suggests that TFP growth does Granger-cause VC investments. Most coefficients on TFP growth are positive and significant, which also supports the finding that innovations cause VC investment.

Although the testing results appear to be sensitive to definitions of VC investment and choices of lag length, at least we can say that there are little evidence for VC-first hypothesis. The results show that TFP growth causes first-round VC investment in dollar amounts, but the converse is not true. In other cases, the directions of causality are somewhat mixed. Hence, in follow-on rounds VC investment and TFP growth may have feedback relations.

3.2 Unobservable Technological Opportunity

So far we have examined the relationship between TFP growth and VC investment using the panel AR. We are now going to extend the analysis including an observable variable that simultaneously affect both TFP growth and VC investment, and "ERISA dummy" and the commitment as explanatory variables for VC investment. The analysis focuses on the robustness of the insignificant effects of VC investment on innovation that has been obtained in the panel AR analysis presented before.

Now we consider the system of equations that can capture the simultaneity of TFP growth and VC investment. Then, we assume that for each industry, current TFP growth is a function of its past values, the previous VC investment, some exogenous variables, and an unobservable common factor, or

$$TFP_t = f(TFP_{t-1,}TFP_{t-2,} \ldots, VC_{t-1}, \mathbf{X}_t, Y_t^*).$$

Similarly, for each industry, current VC investment is a function of past VC commitments, some exogenous variables, and the unobservable common factor, or

$$VC_t = g(COM_{t-1,}COM_{t-2,} \ldots, \mathbf{Z}_t, Y_t^*).$$

The common factor in both functions includes demand shocks to specific industry sectors. A positive demand shock raises TFP growth for the reason described just before and such shock may induce more demands for VC investment because the number of start-up firms presumably rises. For estimation purposes, we specify two functions as the following linear parametric forms

$$TFP_{i,t} = \sum_{j=1}^{J} \alpha_j TFP_{i,t-j} + \sum_{j=1}^{J} \beta_j VC_{i,t-j} + \sum_{n=1}^{N} \delta_n X_{i,t}^n + Y_{i,t}^* + \mu_i' + \epsilon_{i,t}', \quad (3)$$

$$VC_{i,t} = \sum_{l=1}^{L} \phi_l COM_{i,t-l} + \sum_{m=1}^{M} \psi_m Z_{i,t}^m + \rho Y_{i,t}^* + \mu_i'' + \epsilon_{i,t}'', \quad (4)$$

where μ_i and μ_i' are unobserved industry-specific heterogeneities that are assumed to be *random effects* satisfying

$$\begin{aligned}
E\left[\mu_i' | TFP_{t-1}, TFP_{t-2}, \ldots, VC_{t-1}, VC_{t-2}, ..., COM_{t-1}, COM_{t-2}, \ldots, \mathbf{X}_t, \mathbf{Z}_t, Y_t^*\right] &= 0 \\
E\left[\mu_i'' | TFP_{t-1}, TFP_{t-2}, \ldots, VC_{t-1}, VC_{t-2}, ..., COM_{t-1}, COM_{t-2}, \ldots, \mathbf{X}_t, \mathbf{Z}_t, Y_t^*\right] &= 0
\end{aligned}$$

Two idiosyncratic errors $\epsilon_{i,t}'$ and $\epsilon_{i,t}''$ are also assumed to be mutually serially uncorrelated. Eliminating $Y_{i,t}^*$, we have the following reduced form

$$\begin{aligned}
TFP_{i,t} &= \sum_{j=1}^{J} \alpha_l TFP_{i,t-j} + \frac{1}{\rho} VC_{i,t} + \sum_{j=1}^{J} \beta_j VC_{i,t-j} + \sum_{l=1}^{L} \left(-\frac{\phi_l}{\rho}\right) COM_{i,t-l} \\
&\quad + \sum_{n=1}^{N} \delta_n X_{i,t}^n + \sum_{m=1}^{M} \left(-\frac{\psi_m}{\rho}\right) Z_{i,t}^m + \left(\mu_i' - \frac{1}{\rho}\mu_i''\right) + \left(\epsilon_{i,t}' - \frac{1}{\rho}\epsilon_{i,t}''\right) \\
&\equiv \sum_{j=1}^{J} \theta_{1j} TFP_{i,t-j} + \theta_{20} VC_{i,t} + \sum_{j=1}^{J} \theta_{2j} VC_{i,t-j} + \sum_{l=1}^{L} \theta_{3l} COM_{i,t-l} \\
&\quad + \sum_{n=1}^{N} \theta_{4n} X_{i,t}^n + \sum_{m=1}^{M} \theta_{5m} Z_{i,t}^m + \mu_i + \epsilon_{i,t}, \qquad (5)
\end{aligned}$$

where $\mu_i = \mu_i' - \mu_i''/\rho$ is the new random effect, and $\epsilon_{i,t} = \epsilon_{i,t}' - \epsilon_{i,t}''/\rho$ is the new idiosyncratic error.

We are interested in the signs and the joint statistical significance of the coefficients on lagged VC investment, i.e. $(\theta_{21,\ldots,}\theta_{2J}) = (\beta_1, \ldots, \beta_J)$. Unlike the analysis on the causality in the previous section, however, we cannot estimate the equation (5) by GLS, because the explanatory variable $VC_{i,t}$ would generate a simultaneous equation bias if we did so. Then, we take past values of VC investment as instruments, and apply IV regression. Specifically, we estimate the equation by setting the lag length for TFP growth equal to two or four, setting the lag length for VC commitments equal to one, and taking first three or five lags of VC investment as instruments, depending on the lag length of VC investment.

We also include year dummies as exogenous variable $X_{i,t}^n$ on the side of equation (3). This is presumably important because TFP growth is affected by economy-wide shocks. For instance, capacity utilization rates go up during economic boom and as a consequence TFP growth may go up without any technological change because manufacturing plants are now more efficiently operated than during recession.

Furthermore, we introduce, as only an exogenous variable $Z_{i,t}^{m}$ on the side of equation (4), the dummy which takes one before the clarification of ERISA prudent man rule and which takes zero otherwise. 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. Furthermore, in 1979, the highest marginal capital gains tax rate was reduced from 33.8% to 28%. Thus, 1979 is presumably the beginning of the new era for the US VC industry. Therefore, this ERISA dummy is likely to related to the amount of VC investment but there is no reason to believe why this variable is related to TFP growth. Thus, this dummy seems ideal for controlling a possible simultaneity between TFP growth and VC investment.

– Table 6 Here –

Table 6 presents the estimation results of the equation (5). All Wald statistics for testing the exclusion of all lagged VC investment are significant at 1% level. Their coefficients are mostly positive and often significant. Thus, taking into account the simultaneity of TFP growth and VC investment, the results are consistent to the VC-first hypothesis.

4 Concluding Remarks

This paper examined the causality and the simultaneity of innovation and venture capital investment using TFP growth as a measure of innovation. To address these two issues, we studied a panel of U.S. manufacturing industries. The panel AR analyses showed that positive relation between innovation and venture capital investment is likely to come from the positive impact of innovation on venture capital investment (the innovation-first hypothesis) and there is little support for the VC-first hypothesis that venture capital investment causes innovation. However, if we control for the simultaneity of TFP growth and VC investment, the results change; the estimated coefficients are consistent with VC-first hypothesis.

One direction of further research is to extend the empirical study to countries other than the US. One interesting country is Japan. An anecdotal evidence suggests that the Japanese economy experienced business venturing booms both at the beginning of the 80s and at the middle of 90s (Nihon Sangyo Shimbun 1995). These periods coincide with the time when the US venture capital industry also experienced a rapid growth. Thus, it is interesting to examine the data in Japan and see if a similar technological force is driving business venturing. It is also important to look at individual industries to isolate the time series effects from cross sectional effect as some industries are experiencing higher TFP growth than others. Besides, the direction of the causality may differ across industries.

Another direction of further research is to examine the data on business startup. The innovation-first hypothesis boils down to innovation stimulating entrepreneurship and it makes sense to look at the data on entrepreneurship directly. However, one may need to be careful in choosing the entrepreneurship data such that the sample of entrepreneurs represent the types of the entrepreneurs that the innovation-first hypothesis assumes. The scope of the entrepreneurship that the hypothesis assumes is rather limited and there are presumably many other reasons for entrepreneurs to start up own businesses. Empirically, many entrepreneurs are not oriented towards growth.[14] These entrepreneurs may be better described by the marginal entrepreneurs in Lucas (1978). In his model, there is a continuum of individuals each of that faces a decision between starting up his/her own

[14] Hellman and Puri (1998) find that venture-backed firms grow faster than their counterparts in their data gathered in California. Kortum and Lerner (1998) report that in Middlesex County the average employment of venture-backed firms is 526 that is roughly three times as much as the one of non-venture-backed firms.

firm and, employed by a firm and working for a wage. In his model, late-coming entrepreneurs stay relatively small and never threaten incumbents. Ueda (1999) examines the relationship between TFP growth and creation of new plants in U.S. manufacturing industries. The paper finds that TFP growth is indeed positively associated with entry of new plants and exit of old plants, suggesting that innovation favors start-ups and disfavors incumbents as the literature on innovation rivalry predicts.

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Figure 1-A

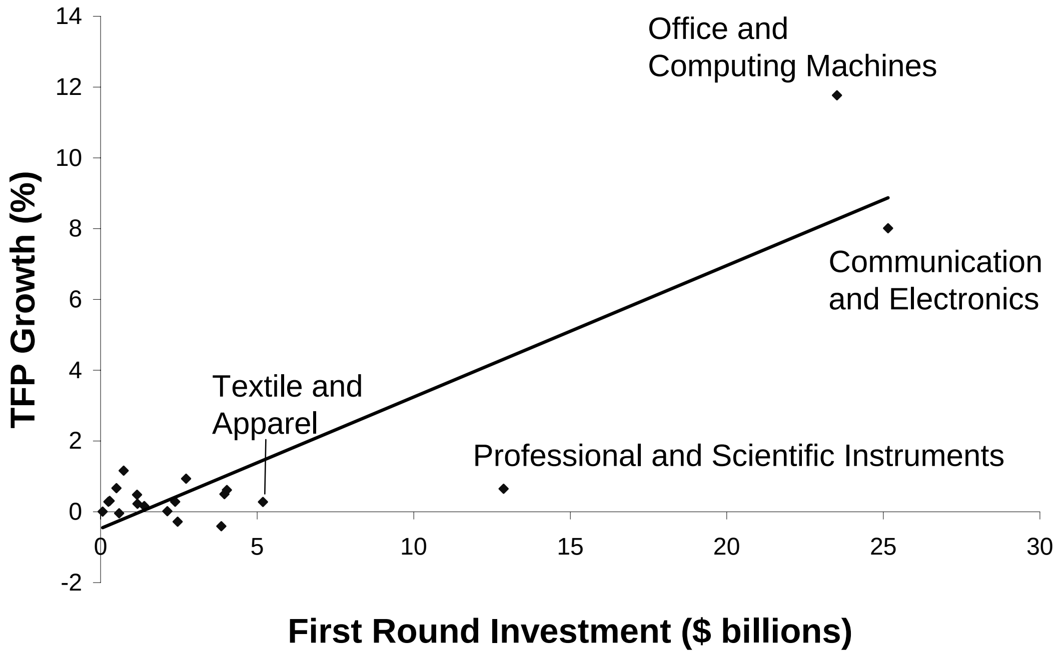

Figure 1-B

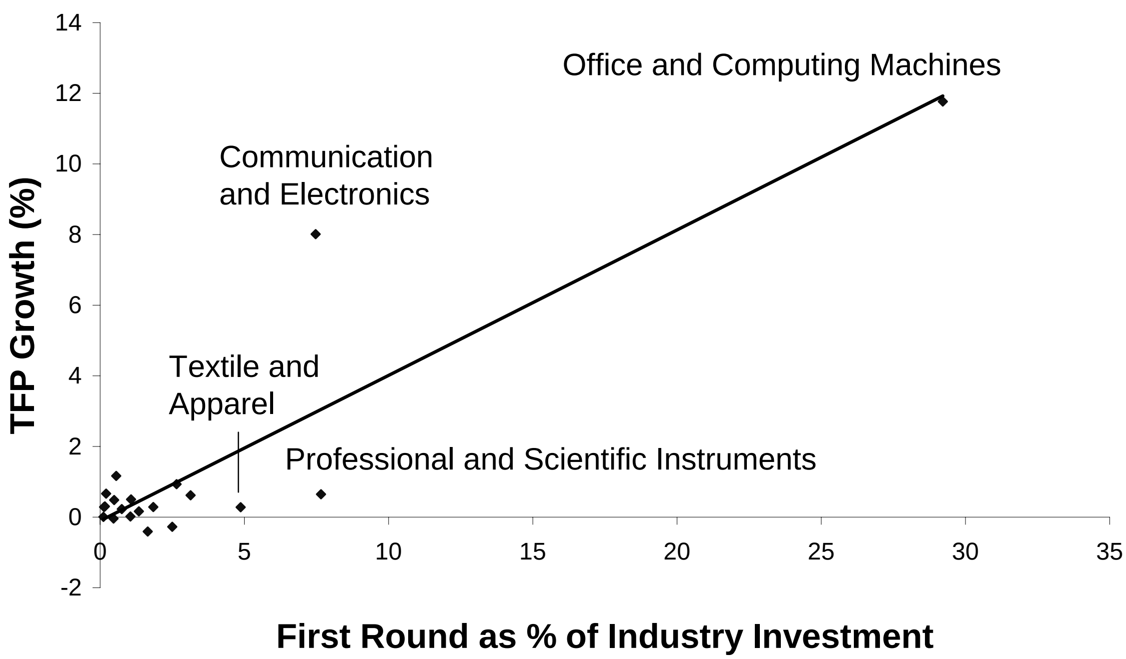

Figure 2-A

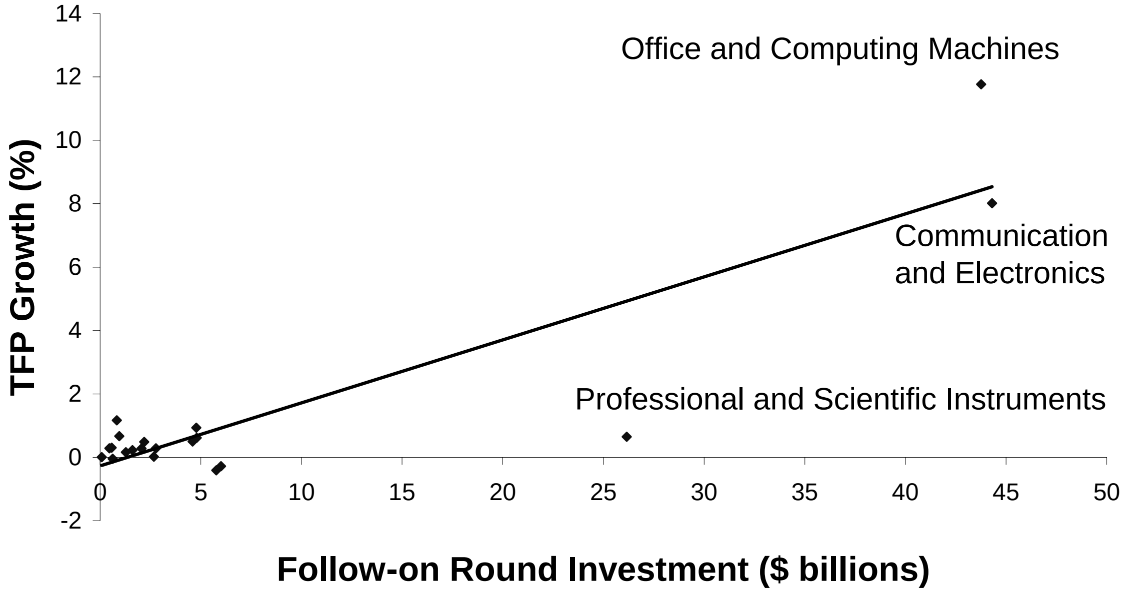

Figure 2-B

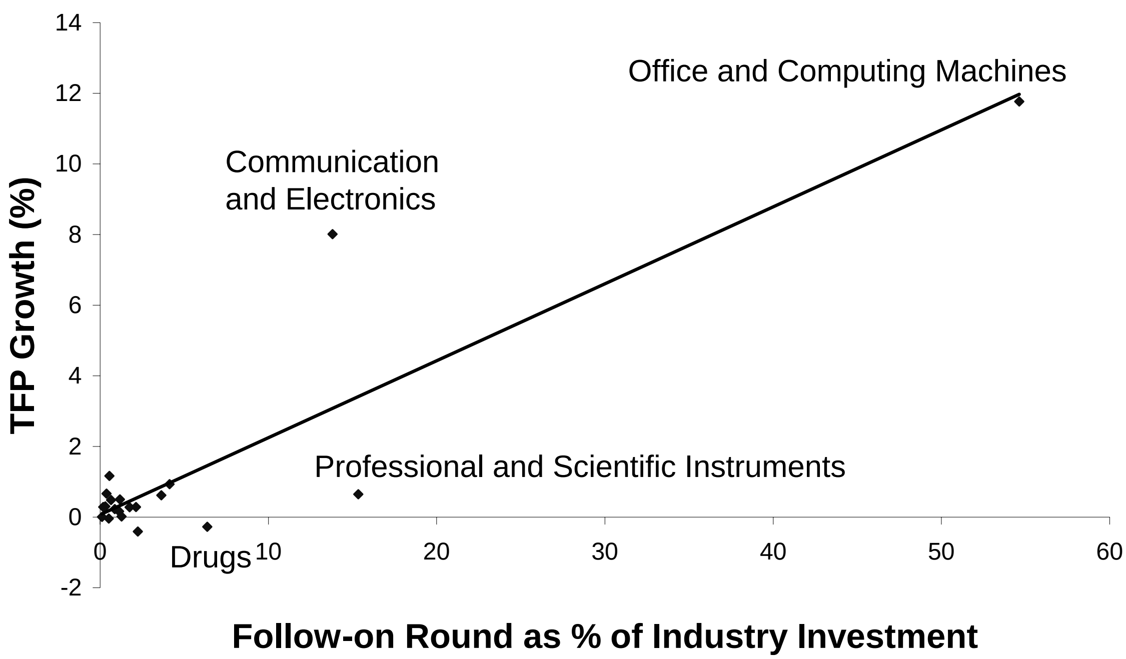

Table 1

Venture capital investments for U.S. manufacturing industries, by industry (millions of 1983 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 Code*	*1965-69*	*1970-74*	*1975-79*	*1980-84*	*1985-89*	*1990-94*	*1995-99*	*2000-01*	*Total*
1	Food and kindred	20	27	68	63	489	1,582	438	3,824	2,055	8,546
2	Textile and apparel	22,23	17	59	103	327	4,259	847	1,417	218	7,248
3	Lumber and furniture	24,25	87	41	79	187	707	313	1,087	176	2,677
4	Paper	26	8	31	31	95	163	24	317	40	710
5	Industrial chemicals	281,282,286	21	20	37	225	409	166	331	251	1,459
6	Drugs	283	5	39	134	691	1,879	1,276	2,459	1,983	8,467
7	Other chemicals	284,285,287-289	12	54	37	108	356	186	1,703	2,699	5,155
8	Petroleum refining and extraction	13,29	11	18	99	481	310	73	212	15	1,217
9	Rubber products	30	13	50	98	177	263	210	578	173	1,562
10	Stone, clay and glass products	32	26	113	69	557	1,697	457	3,852	2,065	8,835
11	Primary metals	33	11	45	54	81	255	182	207	30	864
12	Fabricated metal products	34	22	133	195	312	427	246	819	631	2,784
13	Office and computing machines	357	211	777	657	7,683	9,241	4,754	19,810	24,147	67,280
14	Other non-electrical machinery	351-356,358-359	105	108	335	907	1,106	368	1,307	562	4,797
15	Communication and electronics	366,367	209	605	501	4,569	7,167	4,590	23,473	28,339	69,453
16	Other electrical equipment	361-365,369	33	140	188	743	1,546	830	2,636	1,389	7,505
17	Transportation equipment	371,373-375,379	6	45	60	182	734	190	616	1,527	3,360
18	Aircraft and missiles	372,376	3	4	13	23	19	18	52	17	149
19	Professional and scientific instruments	38	78	338	365	2,342	5,897	5,334	14,738	9,935	39,028
20	Other machinery	21,27,31,39	38	131	115	668	1,907	885	3,934	1,943	9,623
	Total		943	2,820	3,233	20,846	39,922	21,388	83,373	78,193	250,718

Table 2

Venture capital commitments by industry for U.S. manufacturing industries (millions of 1983 dollars). Venture capital commitments by industry refer to the million dollar amount available for venture capital funds to invest in U.S. companies of each industry and in each year.

#	*Industry*	*SIC Code*	*1965-69*	*1970-74*	*1975-79*	*1980-84*	*1985-89*	*1990-94*	*1995-99*	*2000-01*	*Total*
1	Food and kindred	20	0.18	25	24	31	174	102	1,652	1,466	3,474
2	Textile and apparel	22,23	0.29	15	37	20	376	222	468	145	1,283
3	Lumber and furniture	24,25	0.51	13	39	13	78	64	227	174	608
4	Paper	26	0.01	10	6	6	26	8	115	44	216
5	Industrial chemicals	281,282,286	0.01	3	10	10	37	21	77	187	345
6	Drugs	283	0.01	2	22	37	295	276	996	1,449	3,077
7	Other chemicals	284,285,287-289	0.14	11	8	5	30	34	721	1,704	2,511
8	Petroleum refining and extraction	13,29	0.15	12	23	59	33	12	55	3	199
9	Rubber products	30	0.06	10	13	12	45	49	205	86	420
10	Stone, clay and glass products	32	0.05	11	7	4	22	35	128	441	648
11	Primary metals	33	0.02	13	16	6	43	54	68	25	226
12	Fabricated metal products	34	0.09	35	29	18	82	243	325	191	922
13	Office and computing machines	357	1.98	231	180	732	1,732	1,357	11,536	23,838	39,609
14	Other non-electrical machinery	351-356,358-359	0.47	35	68	49	136	86	382	244	1,000
15	Communication and electronics	366,367	1.21	139	117	443	1,424	1,398	13,936	29,964	47,422
16	Other electrical equipment	361-365,369	0.23	23	32	59	221	200	1,007	794	2,337
17	Transportation equipment	371,373-375,379	0.03	11	13	13	101	42	218	534	933
18	Aircraft and missiles	372,376	0.01	1	2	1	3	4	26	22	59
19	Professional and scientific instruments	38	0.98	103	81	222	1,132	1,613	6,881	9,365	19,398
20	Other machinery	21,27,31,39	0.23	17	27	54	307	212	1,186	1,100	2,905
	Total		6.66	720	756	1,795	6,297	6,032	40,208	71,775	127,591

Table 3

Dollar amount and the ratio to industry investment of venture capital investments for U.S. manufacturing industries, by industry. All dollar figures are in billions of 1983 dollars.

	Panel A: Venture Capital Investment 1983 billion of dollars					
	Industry	Mean	Median	Minimum	Maximum	Std. Dev.
1	Food and kindred	0.231	0.078	0.000	1.962	0.429
2	Textile and apparel	0.196	0.055	0.000	3.444	0.563
3	Lumber and furniture	0.072	0.047	0.000	0.367	0.084
4	Paper	0.019	0.008	0.000	0.151	0.032
5	Industrial chemicals	0.039	0.023	0.000	0.150	0.040
6	Drugs	0.229	0.172	0.000	1.059	0.271
7	Other chemicals	0.139	0.024	0.000	2.057	0.394
8	Petroleum refining and extraction	0.033	0.012	0.000	0.142	0.041
9	Rubber products	0.042	0.032	0.000	0.229	0.045
10	Stone, clay and glass products	0.239	0.086	0.000	1.983	0.432
11	Primary metals	0.023	0.014	0.000	0.141	0.028
12	Fabricated metal products	0.075	0.050	0.000	0.477	0.088
13	Office and computing machines	1.818	0.923	0.007	17.668	3.250
14	Other non-electrical machinery	0.130	0.105	0.001	0.456	0.115
15	Communication and electronics	1.877	0.760	0.009	20.832	3.906
16	Other electrical equipment	0.203	0.130	0.000	0.983	0.246
17	Transportation equipment	0.091	0.037	0.000	1.394	0.231
18	Aircraft and missiles	0.004	0.002	0.000	0.016	0.004
19	Professional and scientific instruments	1.055	0.628	0.001	5.885	1.413
20	Other machinery	0.260	0.112	0.000	1.928	0.402

	Panel B: Venture Capital Investment / Capital Expenditure					
	Industry	Mean	Median	Minimum	Maximum	Std. Dev.
1	Food and kindred	2.25%	0.95%	0.00%	13.73%	3.26%
2	Textile and apparel	6.61%	2.13%	0.00%	124.60%	20.20%
3	Lumber and furniture	2.47%	1.99%	0.00%	9.44%	2.22%
4	Paper	0.33%	0.19%	0.00%	1.62%	0.40%
5	Industrial chemicals	0.58%	0.31%	0.00%	2.44%	0.59%
6	Drugs	8.86%	7.33%	0.00%	24.69%	7.27%
7	Other chemicals	3.97%	1.14%	0.00%	50.81%	9.28%
8	Petroleum refining and extraction	0.98%	0.45%	0.00%	4.40%	1.20%
9	Rubber products	1.11%	0.92%	0.00%	3.26%	0.69%
10	Stone, clay and glass products	6.78%	3.04%	0.00%	39.19%	9.54%
11	Primary metals	0.47%	0.38%	0.00%	3.02%	0.56%
12	Fabricated metal products	1.63%	1.41%	0.00%	5.86%	1.16%
13	Office and computing machines	83.84%	45.99%	3.80%	730.97%	131.63%
14	Other non-electrical machinery	2.33%	1.85%	0.07%	5.82%	1.61%
15	Communication and electronics	21.28%	15.15%	1.64%	103.19%	20.02%
16	Other electrical equipment	6.78%	4.68%	0.00%	24.97%	6.24%
17	Transportation equipment	1.14%	0.51%	0.00%	11.25%	2.04%
18	Aircraft and missiles	0.22%	0.17%	0.01%	0.92%	0.19%
19	Professional and scientific instruments	22.99%	15.25%	0.27%	97.70%	22.82%
20	Other machinery	3.88%	2.54%	0.00%	22.16%	4.60%

Table 3 (Continued)

TFP growth 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	0.5%	0.5%	-2.8%	3.2%	1.3%
2	Textile and apparel	0.3%	0.5%	-13.6%	4.4%	2.8%
3	Lumber and furniture	0.2%	0.2%	-5.7%	4.1%	2.1%
4	Paper	0.3%	0.9%	-6.3%	3.9%	2.4%
5	Industrial chemicals	0.7%	0.8%	-10.8%	8.4%	4.3%
6	Drugs	-0.3%	-0.5%	-8.8%	7.7%	3.3%
7	Other chemicals	0.3%	0.7%	-4.4%	8.5%	2.7%
8	Petroleum refining and extraction	0.0%	0.7%	-15.3%	10.6%	4.8%
9	Rubber products	1.2%	1.3%	-5.1%	5.1%	2.4%
10	Stone, clay and glass products	0.6%	1.2%	-6.1%	5.8%	2.7%
11	Primary metals	0.3%	0.5%	-9.9%	6.5%	3.0%
12	Fabricated metal products	0.2%	0.5%	-4.2%	4.0%	2.1%
13	Office and computing machines	11.8%	11.5%	-1.9%	41.0%	9.4%
14	Other non-electrical machinery	0.0%	0.0%	-6.5%	5.6%	2.6%
15	Communication and electronics	8.0%	4.1%	-3.9%	35.7%	10.4%
16	Other electrical equipment	0.9%	1.2%	-4.7%	4.8%	2.3%
17	Transportation equipment	0.5%	0.4%	-6.5%	7.2%	3.0%
18	Aircraft and missiles	0.0%	0.0%	-6.7%	7.3%	2.9%
19	Professional and scientific instruments	0.6%	0.5%	-3.0%	4.8%	1.9%
20	Other machinery	-0.4%	-0.7%	-5.4%	4.0%	2.1%

Table 4-A

Do venture capital investment cause innovation? Dependent variables are TFP growth. Independent variables are lagged TFP growth and lagged terms of various measures of venture capital investments. Sample period is 1965-2001. First Round refers to venture capital investments made in companies that have never received venture capital financing before. Follow-on refers to venture capital investments made in companies that have received venture capital financing before. CAPX refers to capital investment. Estimation methods are generalized least squares with random effects. Constants are not reported. Figures with *, **, and *** are significant at 10%, 5%, and 1% level. Standard errors (Eicker-White formula) are in parenthesis. The null hypothesis for Wald test is that all coefficients on venture capital investments are zero.

	First Round		First Round/CAPX		Follow-on Round		Follow-on Round/CAPX	
	(a)	**(b)**	**(c)**	**(d)**	**(e)**	**(f)**	**(g)**	**(h)**
VC(-1)	-0.3871	-1.1440*	-0.0160	-0.0445**	-1.2198	-1.2091	-0.0181	-0.0114
	(0.8377)	(0.6808)	(0.0249)	(0.0203)	(1.3393)	(1.1750)	(0.0191)	(0.0156)
VC(-2)	0.7859	-0.1756	0.0401	0.0032	2.6055	0.2243	0.0558*	-0.0513
	(0.7624)	(0.4943)	(0.0428)	(0.0167)	(1.6898)	(2.4072)	(0.0326)	(0.0430)
VC(-3)		1.0839		0.0382		2.3558		0.0931***
		(1.0619)		(0.0415)		(2.4577)		(0.0208)
VC(-4)		1.1969		0.0577		-0.1049		0.0186
		(0.8883)		(0.0474)		(1.2179)		(0.0296)
TFP(-1)	0.5161***	0.4468***	0.5135***	0.4299***	0.4956***	0.4331***	0.4946***	0.4275***
	(0.0929)	(0.0784)	(0.0865)	(0.0733)	(0.0899)	(0.0769)	(0.0950)	(0.0812)
TFP(-2)	0.2147***	0.1183*	0.2094***	0.1076*	0.1993**	0.1137*	0.1931***	0.0887*
	(0.0786)	(0.0628)	(0.0645)	(0.0551)	(0.0842)	(0.0677)	(0.0660)	(0.0480)
TFP(-3)		0.1981***		0.1938***		0.1903***		0.1766***
		(0.0527)		(0.0534)		(0.0518)		(0.0585)
TFP(-4)		0.1788***		0.1787***		0.1755***		0.1763***
		(0.0341)		(0.0386)		(0.0328)		(0.0377)
Wald Test (df)	1.09 (2)	7.57 (4)	0.88 (2)	19.93*** (4)	5.14* (2)	10.59** (4)	3.18 (2)	157.00*** (4)

Table 4-B

Does innovation cause venture capital investment? Dependent variables are various measures of venture capital investments. Independent variables are lagged TFP growth and lagged dependent variables. Sample period is 1965-2001. First Round refers to venture capital investments made in companies that have never received venture capital financing before. Follow-on refers to venture capital investments made in companies that have received venture capital financing before. CAPX refers to capital investment. Estimation methods are generalized least squares with random effects. Constants are not reported. Figures with *, **, and *** are significant at 10%, 5%, and 1% level. Standard errors (Eicker-White formula) are in parenthesis. The null hypothesis for Wald test is that all coefficients on TFP growth are zero.

Dependent Variable	**First Round**		**First Round/CAPX**		**Follow-on Round**		**Follow-on Round/CAPX**	
	(a)	**(b)**	**(c)**	**(d)**	**(e)**	**(f)**	**(g)**	**(h)**
TFP(-1)	0.0237***	0.0220***	0.3469**	0.3017*	0.0372***	0.0285***	0.7416	0.6959
	(0.0087)	(0.0074)	(0.1469)	(0.1756)	(0.0130)	(0.0074)	(0.4884)	(0.5080)
TFP(-2)	0.0198***	0.0208***	0.5409*	0.5351	0.0227***	0.0241***	0.6048	0.5041
	(0.0049)	(0.0061)	(0.3155)	(0.3470)	(0.0068)	(0.0076)	(0.4684)	(0.3459)
TFP(-3)		-0.0066		-0.0694		-0.0134		-0.2711
		(0.0087)		(0.2301)		(0.0130)		(0.2991)
TFP(-4)		0.0073		0.1240		0.0135		0.1954***
		(0.0082)		(0.0911)		(0.0097)		(0.0702)
VC(-1)	0.4138***	0.3970***	0.5234***	0.5135***	0.5125***	0.7869***	0.8077***	0.9831***
	(0.0552)	(0.0566)	(0.0595)	(0.0920)	(0.1160)	(0.2320)	(0.0659)	(0.1201)
VC(-2)	0.2248	0.1255	0.2300***	0.1833***	0.1499	-1.3386*	-0.2098	-0.9849***
	(0.1985)	(0.2166)	(0.0434)	(0.0195)	(0.3350)	(0.6948)	(0.2850)	(0.3357)
VC(-3)		0.1587*		0.0575		2.6902***		0.8162***
		(0.0873)		(0.0921)		(0.7366)		(0.0720)
VC(-4)		0.2212		0.1315		-1.1730***		0.0709*
		(0.1560)		(0.0950)		(0.3984)		(0.0396)
Wald Test (df)	16.25*** (2)	35.91*** (4)	85.31*** (2)	77.74*** (4)	11.20*** (2)	75.51*** (4)	5.56* (2)	29.09*** (4)

Table 5-A

Do venture capital investment cause innovation? Dependent variables are TFP growth. Independent variables are lagged TFP growth and lagged terms of various measures of venture capital investments. Sample period is 1965-2001. First Round refers to venture capital investments made in companies that have never received venture capital financing before. Follow-on refers to venture capital investments made in companies that have received venture capital financing before. CAPX refers to capital investment. Estimation methods are maximum likelihood. Constants are not reported. Figures with *, **, and *** are significant at 10%, 5%, and 1% level. Standard errors are in parenthesis. The null hypothesis for likelihood ratio test is that all coefficients on venture capital investments are zero.

	First Round		**First Round/CAPX**		**Follow-on Round**		**Follow-on Round/CAPX**	
	(a)	**(b)**	**(c)**	**(d)**	**(e)**	**(f)**	**(g)**	**(h)**
VC(-1)	0.0096	-1.1440**	-0.0135	-0.0445***	-0.4237	-1.2091*	0.0023	-0.0114
	(0.5316)	(0.5478)	(0.0152)	(0.0158)	(0.6303)	(0.6308)	(0.0170)	(0.0174)
VC(-2)	0.2606	-0.1756	0.0063	0.0032	1.3037	0.2243	-0.0048	-0.0513
	(0.9298)	(0.9700)	(0.0282)	(0.0281)	(1.0186)	(1.3710)	(0.0323)	(0.0377)
VC(-3)		1.0839		0.0382		2.3558		0.0931**
		(1.0155)		(0.0285)		(1.8070)		(0.0403)
VC(-4)		1.1969		0.0577**		-0.1049		0.0186
		(1.0074)		(0.0281)		(1.5735)		(0.0358)
TFP(-1)	0.4295***	0.4468***	0.4333***	0.4299***	0.4231***	0.4331***	0.4323***	0.4275***
	(0.0414)	(0.0396)	(0.0404)	(0.0394)	(0.0416)	(0.0400)	(0.0404)	(0.0397)
TFP(-2)	0.1326***	0.1183***	0.1478***	0.1076**	0.1241***	0.1137***	0.1384***	0.0887**
	(0.0442)	(0.0441)	(0.0420)	(0.0436)	(0.0452)	(0.0444)	(0.0424)	(0.0442)
TFP(-3)		0.1981***		0.1938***		0.1903***		0.1766***
		(0.0459)		(0.0457)		(0.0461)		(0.0457)
TFP(-4)		0.1788***		0.1787***		0.1755***		0.1763***
		(0.0467)		(0.0467)		(0.0467)		(0.0469)
Likelihood Ratio Test (df)	0.21 (2)	7.09 (4)	0.95 (2)	12.67** (4)	3.54 (2)	8.96* (4)	0.02 (2)	15.18*** (4)

Table 5-B

Does innovation cause venture capital investment? Dependent variables are various measures of venture capital investments. Independent variables are lagged TFP growth and lagged dependent variables. Sample period is 1965-2001. First Round refers to venture capital investments made in companies that have never received venture capital financing before. Follow-on refers to venture capital investments made in companies that have received venture capital financing before. CAPX refers to capital investment. Estimation methods are maximum likelihood. Constants are not reported. Figures with *, **, and *** are significant at 10%, 5%, and 1% level. Standard errors are in parenthesis. The null hypothesis for likelihood ratio test is that all coefficients on TFP growth are zero.

Dependent Variable	**First Round**		**First Round/CAPX**		**Follow-on Round**		**Follow-on Round/CAPX**	
	(a)	**(b)**	**(c)**	**(d)**	**(e)**	**(f)**	**(g)**	**(h)**
TFP(-1)	0.0237***	0.0220***	0.3469***	0.3017***	0.0378***	0.0287***	0.7403***	0.6959***
	(0.0035)	(0.0037)	(0.0968)	(0.1054)	(0.0049)	(0.0046)	(0.1294)	(0.1316)
TFP(-2)	0.0198***	0.0208***	0.5409***	0.5351***	0.0235***	0.0244***	0.6094***	0.5041***
	(0.0038)	(0.0042)	(0.1054)	(0.1168)	(0.0054)	(0.0052)	(0.1384)	(0.1462)
TFP(-3)		-0.0066		-0.0694		-0.0130**		-0.2711*
		(0.0043)		(0.1223)		(0.0056)		(0.1513)
TFP(-4)		0.0073*		0.1240		0.0138**		0.1954
		(0.0044)		(0.1252)		(0.0056)		(0.1553)
VC(-1)	0.4138***	0.3970***	0.5234***	0.5135***	0.5129***	0.7843***	0.8223***	0.9831***
	(0.0491)	(0.0517)	(0.0399)	(0.0424)	(0.0738)	(0.0715)	(0.0569)	(0.0575)
VC(-2)	0.2248***	0.1255	0.2300***	0.1833**	0.1399	-1.3392***	-0.2715**	-0.9849***
	(0.0855)	(0.0915)	(0.0704)	(0.0753)	(0.1187)	(0.1493)	(0.1107)	(0.1248)
VC(-3)		0.1587*		0.0575		2.6861***		0.8162***
		(0.0957)		(0.0763)		(0.1989)		(0.1335)
VC(-4)		0.2212**		0.1315*		-1.1671***		0.0709
		(0.0950)		(0.0752)		(0.1768)		(0.1185)
Likelihood Ratio Test (df)	132.49*** (2)	123.22*** (4)	81.04*** (2)	69.17*** (4)	135.78*** (2)	132.32*** (4)	87.04*** (2)	80.31*** (4)

Table 6

Does venture capital investment cause innovation? Dependent variables are TFP growth. Independent variables are auto regressive terms and of various measures of venture capital investments. Sample period is 1965-2001. First Round refers to venture capital investments made in companies that have never received venture capital financing before. Follow-on refers to venture capital investments made in companies that have received venture capital financing before. CAPX refers to capital investment. Estimation methods are IV regression with first three or five lags of venture capital investment used as instruments. Current value of venture capital investment, ERISA dummy, which takes 1 after 1980 and 0 before, and year dummies are not reported. Figures with *, **, and *** are significant at 10%, 5%, and 1% level. Standard errors (Eicker-White formula) are in parenthesis. Estimate of ρ and its standard error are calculated by the delta method. The null hypothesis for Wald test is that all coefficients on lagged venture capital investments are zero.

	First Round		First Round/CAPX		Follow-on Round		Follow-on Round/CAPX	
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
VC(-1)	0.9391	-0.0408	0.0035	-0.0244*	1.6023*	0.1891	-0.0008	0.0026
	(1.1300)	(0.5439)	(0.0112)	(0.0141)	(0.8957)	(0.9411)	(0.0207)	(0.0187)
VC(-2)	1.8802**	1.1371**	0.0706	0.0405**	1.5684	1.7658	0.0617**	-0.0140
	(0.9551)	(0.5358)	(0.0473)	(0.0192)	(1.1981)	(2.2036)	(0.0298)	(0.0382)
VC(-3)		0.7654		0.0345		0.1012		0.0926***
		(0.6263)		(0.0320)		(1.9075)		(0.0201)
VC(-4)		0.9635***		0.0521		-0.3692		-0.0176
		(0.3371)		(0.0341)		(0.7661)		(0.0248)
TFP(-1)	0.4944***	0.4077***	0.5341***	0.4257***	0.4712***	0.3994***	0.5165***	0.4333***
	(0.0915)	(0.0867)	(0.0926)	(0.0836)	(0.0884)	(0.0867)	(0.1086)	(0.1009)
TFP(-2)	0.2474***	0.1172**	0.2818***	0.1500***	0.2292***	0.1208**	0.2693***	0.1332***
	(0.0581)	(0.0512)	(0.0612)	(0.0512)	(0.0575)	(0.0541)	(0.0584)	(0.0471)
TFP(-3)		0.2578***		0.2472***		0.2444***		0.2422***
		(0.0690)		(0.0697)		(0.0679)		(0.0711)
TFP(-4)		0.1405***		0.1671***		0.1248***		0.1705***
		(0.0000)		(0.0000)		(0.0000)		(0.0000)
ρ	1.3757	1.2372	-32.2581	-33.3333	6.0459	2.2017	-58.8235	-42.0168*
	(2.2849)	(1.5197)	(32.1540)	(22.6667)	(29.4512)	(2.9583)	(68.5121)	(23.6565)
Wald Test (df)	29.18*** (2)	40.01*** (4)	33.66*** (2)	36.57*** (4)	28.81*** (2)	22.19*** (4)	159.56*** (2)	372.49*** (4)