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# VENTURE CAPITAL AND INNOVATION: WHICH IS FIRST?

Masayuki Hirukawa *Setsunan University*
Masako Ueda* *Northwestern University*

*Abstract.* Policy-makers typically interpret positive relations between venture capital (VC) investments and innovations as evidence that VC investments stimulate innovation (*VC-first hypothesis*). This interpretation is, however, one-sided because there may be a reverse causality that innovations induce VC investments (*innovation-first hypothesis*): an arrival of new technology increases demand for VC. We analyze this causality issue of VC and innovation in the US manufacturing industry using both total factor productivity growth and patent counts as measures of innovation. We find that, consistent with the innovation-first hypothesis, total factor productivity growth is often positively and significantly related with future VC investment. We find little evidence that supports the VC-first hypothesis.

JEL Classifications: G24, D24, O31, O32.

## 1. INTRODUCTION

Policy-makers who aim to stimulate economic growth often attempt to create or expand their local venture capital (VC) industries. These attempts include the Yozma program in Israel, the Small Business Investment Company (SBIC) program in the United States, and various initiatives to create stock markets where listing requirements are less stringent than in 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 small and new firms than otherwise and thereby encourage innovations (see e.g. European Commission, 1995, Venture Enterprise Center, Ministry of International Trade and Industry, 1991, for Japan).

There is indeed both ad hoc and academic evidence suggesting that firms grow fast and can circumvent the issue of underinvestment in innovative activities if

**Address for Correspondence*: Kellogg School of Management, Northwestern University, 2001 Sheridan Road, Evanston, IL 60208-2009, USA. E-mail: m-ueda@kellogg.northwestern.edu. Previously, this paper was circulated under the title, ‘Does innovation spur venture capital?’ We thank Bruno Cassiman, Marco Da Rin, Mariassunta Giannetti, Bronwyn Hall, Dietmar Harhoff, the Managing Editor, two anonymous referees, and the seminar participants at the CESifo Conference on Venture Capital and Public Policy, the TMR Euroconference, the 1999 SED meetings, Oxford University, and Stockholm School of Economics for helpful comments, and Giovanni Cespa for valuable suggestions. We also thank Norm Morin at the Federal Reserve Board for providing the manufacturing real net capital stock dataset. All remaining errors are ours.

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

they are backed by venture capitalists. At firm level, Hellmann and Puri (2000) and Engel (2002) find that VC-backed firms grow faster than their industry counterparts. Venture-backed firms in Japan have also experienced rapid growth (Suzuki, 1996). Regarding innovation, Kortum and Lerner (2001) find that patents granted to VC-backed companies are cited more often than other patents, suggesting that VC-backed companies are engaged in important innovative activities. At industry level, Kortum and Lerner (2001) find that in the United States, VC investments have a stronger impact on patent counts than R&D expenditure. Using German data, Tykvova (2000) also finds a positive relation between VC investment and patent application.[2]

A common interpretation of the results found in the literature cited above is that 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: arrivals of significant innovation opportunities stimulate new firm start-ups to exploit such opportunities and these start-ups demand VC because venture capitalists are complements to such firms.

There are two reasons why new firms as opposed to established firms often exploit significant innovation opportunities. First, an arrival of a significant innovation may create business opportunities and trigger firm start-ups. 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 in the 1980s and later Dell, emerged and entered the market that used to be dominated by IBM. Second, it is argued in the rich literature on industrial organization 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 (e.g. Reinganum, 1983; Gans and Stern, 2000).

The complementarity between new firms that exploit significant innovation opportunities and VC might 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, VC may have high flexibility in terms of financial instruments because VC industries are relatively free from regulations. The financial instrument most commonly used by venture capitalists is convertible debts. Banks are not allowed to use such equity instruments. Cornelli and Yosha (2003) show how convertible debts can lessen the entrepreneur's incentive to engage in 'window dressing' or short-termism. Third, besides financing portfolio firms, VC often supplies firms with other resources essential to new firms. Such resources include legal and marketing expertise, and are invaluable for new firms whose assets typically consist of their blueprints of prospective projects alone.

[2] There is other evidence that supports the role of venture-backed firms in driving innovation and growth. According to the National Venture Capital Association (1998), 80% of venture capital investment is towards high-technology industries, such as computers, communications, medical and health, and biotechnology.

New firms typically lack many types of resources that large firms internalize by taking advantage of their scale economies and business history. For instance, Lerner (1995) finds that venture-backed firms are more likely to file lawsuits related to trade secrecy infringement and suggests that venture capitalists actively help portfolio firms with such 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 that venture capitalists can help new firms to find marketing channels and customers.

Given that significant innovation opportunities stimulate new firm start-ups and these start-ups demand VC, we hypothesize that innovations spur the VC market, via stimulating new firm start-up. In contrast to the VC-first hypothesis, we refer to this view as the *innovation-first hypothesis*.

This paper addresses the causality issues described above by studying dynamic panel data for US manufacturing industries. We study two types of VC investment measures (the first and the follow-on investments) and two types of innovation measures (total factor productivity (TFP) growth and patent counts). Using a panel autoregressive (AR) model, we begin by testing for Granger-type causality between innovation and VC investment. We also examine AR models individually for each of the 5 VC-intensive industries.

We find weak evidence for the VC-first hypothesis when TFP growth is used as the measure of innovation. In particular, the estimated panel AR models under various specifications indicate that 2-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 1-year lagged VC investment is negatively and often significantly related with both TFP growth and patent counts. Several theories explain the VC's negative impact on innovation. First, significant amounts of capital that VC provide might promote entrepreneurs to make inefficient strategic decisions. For instance, abundant financial resources might reinforce managerial optimism, resulting in inefficient strategic decisions (e.g. Kahneman and Lovallo, 1993; deMeza and Southey, 1996). Abundant financial resources might also allow escalation of commitment (defending and continuing a course of action in spite of negative outcomes), as advocated by Ross and Staw (1993). Consistent with these theories, George (2005), who analyses privately-held firms in the United States, finds that profitability declines when firms have a large amount of assets. Second, 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 a VC investment boom leads to a slowdown in TFP growth. Third, the negative relation between lagged VC investment and patent counts is consistent with the firm-level evidence of Engel and Keilbach (2007) and Caselli *et al.* (2009). Using German data and Italian data, respectively, these two papers find that after receiving VC financing, the firms experience high sales growth but patenting slows down. One explanation behind these findings is that venture capitalists change the strategy of their portfolio firms from innovating to cashing out from innovation.

We find some evidence for the innovation-first hypothesis when TFP growth is used as the measure of innovation. In particular, estimating the panel AR models and the AR model 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 the literature on financial development and growth. For instance, close to the spirit of this paper, Robinson (1952) argues that financial development follows economic development. Greenwood and Jovanovic (1999) rigorously model how economic growth and financial development are mutually dependent. Levine *et al.* (2000) find that exogenous development of financial intermediary sectors enhances economic growth. Compared to the literature on banking sectors and stock markets, there exist few academic studies on the economic impact of VC. One important exception is Zucker *et al.* (1998), who study the causes of biotechnology start-up firms. Interestingly, they find that controlling for the presence of local star scientists, the size of the VC market negatively affects the rate of biotechnology start-up.

The rest of the paper is organized as follows. Section 2 describes the data used in this paper, and details how we construct the data set for analysis. Section 3 presents the results of empirical analyses. Section 4 concludes. The Appendix explains how we construct the proxy for VC commitment.

## 2. DATA DESCRIPTION

As measures of innovation, we use both TFP growth and patent counts. It is interesting to study both of these innovation measures for the following reason. An important difference between TFP growth and patent counts is that TFP growth results from adopting new technology, whereas patents are based on ideas about new technology that has not necessarily been adopted yet. Therefore, if VC investment is used for generating new technology ideas rather than using new technology, we expect the VC-first hypothesis to hold for patent counts but not for TFP growth. If VC investment is used for adopting new technology instead of creating it, we expect 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 follow-on investments to have bigger impacts on innovation than first round investments. When we test for the innovation-first hypothesis, we expect it to hold better for first round investments than for 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 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 VC data and TFP data. The second challenge is extending the TFP data series beyond the period over which the National Bureau of Economic Research (NBER) originally constructed them.

### 2.1. *Data sources*

The data analyzed in the present paper come from four main data sources: VentureXpert; Bartelsman, 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 the 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 Standard Industrial Classsification (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 hand-collection. 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 the Census Bureau and contains productivity related variables for all manufacturing industries at the SIC four-digit level.[3] The data are annual, start from 1958 and end in as early as 1996, which limits one from extending an analysis into recent years. To study the impact of rapid increases in VC investment on TFP growth in the late 1990s, we extend the NBER productivity database up to 2001 using the method described in the next section. The NBER productivity database

[3] Bartelsman and Gray (1996) provide a detailed description of this NBER productivity database.

covers only manufacturing. Thus, we limit our scope to manufacturing industries.

The NBER patent database and its extension contain information on utility patents granted at the U.S. Patent and Trademark Office (USPTO) from 1963 to 2002.[4,5] For our empirical analysis, we sort the patent data by year of application instead of 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 for a patent to be granted. Therefore, we also extract updated data from the patent bibliographic raw files at USPTO.[6]

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

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

We extend the NBER productivity database and VC investment data, tabulated according to KL classification, up to 2001. The reason for the extension is to include the impact of unprecedented increases in VC investment in the late 1990s. 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).[7]

#### 2.2.1. *Extension and modification of NBER productivity database*

We use the NBER's five-factor (production labor hours, non-production workers, capital, energy and non-energy material) productivity as our measure of TFP.[8] The original NBER productivity database contains this TFP series up to 1996. To include the later 1990s period in our study, when the US VC industry experienced an explosive growth, we extend both TFP and capital expenditure series up to 2001.

[4] The extension is downloadable from the Bronwyn Hall's website (http://elsa.berkeley.edu/users/bhhall/bhdata.html). This extension has the primary international classification, which is not present in the original NBER patent database. We compile the patent data by SIC code using the concordance between the primary international classification and SIC developed by Brian Silverman. (http://www.rotman.utoronto.ca/~silverman/ipcsic/documentation_IPC-SIC_concordance.htm)

[5] See Hall *et al*. (2005) for the details of these patent databases.

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

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

[8] The deflated value of shipment is defined as the real output, and the 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.

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 the Census Bureau. 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 source 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 the Capital Flow Table from the Bureau of Economic Analysis. For other types of shipment and energy and non-energy material, we use the 1997 Benchmark Input-Output Accounts and use tables from the 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 the producer price index and the consumer price index from the 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 four-digit SIC system, whereas, for every dataset after 1996, the industry classification is based on the six-digit North American Industry Classification System (NAICS). The KL industry classification is, roughly speaking, a two-digit SIC system. As the KL industry classification is coarser than the four-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 using the NBER productivity database.

The KL industry classification is not always coarser than the six-digit NAICS; that is, two establishments that share the same six-digit NAICS might belong to different KL industries. To convert the six-digit NAICS figures into those based on the KL industry classification, we first use the bridge table between four-digit SIC and six-digit NAICS as of 1997 published by the Census Bureau. Number of employees and average number of production workers are converted on the basis of the bridge table for 'Paid Employees'. Annual payroll and production worker wages are converted on the basis of the bridge table for 'Annual Payroll'. All others are converted on the basis of the bridge table for 'Sales, Receipts, or Shipments'. The four-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 the 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).[9] These industries all belong to 'Others' in the KL industry classification scheme and, as a consequence, we dropped 'Others' from our analysis. Therefore, the original KL industry classification scheme contains 20 industries, whereas our analysis is focused on 19 industries. Second, whereas new capital expenditures are directly available in the NBER productivity database, the latest ASM does not distinguish new and used capital expenditures; instead, it provides the sum of the capital expenditures for each industry. Then, we estimate the new capital expenditure of each four-digit SIC by using the share of the industry's new capital expenditure 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 make up a significant portion of employers' labor cost, and their importance has grown over the past two decades. For instance, they constituted 10.8% of total pay in 1968 and grew to 21% in 2001. Therefore, if we were to 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 employers' social security contribution and fringe benefit from the ASM.

### 2.3. *Descriptive statistics*

Table 1 shows that VC investments in the US manufacturing industry have dramatically grown during the past four decades, in terms of both dollar amounts and ratios to privately-funded R&D expenditures. The amount of investment in 1999–2001 is approximately 100 times as much as that in 1968–1970. Notably, stimulated by a sequence of regulatory changes favorable to VC, the investment amount significantly increased from the 1970s to the 1980s. These changes involve clarification of the "prudent man rule" of the US Department of Labor Employment Retirement Income Security Act (ERISA), the reduction of the capital gains tax rate,[10] and the introduction of the *Bayh–Dole Act*, which facilitated technology transfer from universities to private sectors.[11] The whole VC industry experienced a downturn in the early 1990s as a result of pension funds' asset quality problems. Pension funds were pulled out from private equity investments to reduce the riskiness of their portfolios. Pension funds are major financing sources for US venture capitalists, and this assets reallocation of pension funds severely hit venture capitalists.

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

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

[11] Enactment of the Bayh–Dole Act (P.L. 96-517), the 'Patent and Trademark Act Amendments of 1980', on 12 December 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 that 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).

*Table 1. Summary statistics by year*

| Year | TFP growth (%) | Number of patent applications | Number of firms receiving VC funding | VC investment ($M) | | | VC investment/R&D | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | 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 |

Venture capital (VC) investments refer to the 2001 constant million dollar amount that VC funds invested in US companies of each industry and in each year. 'First round (VC)' refers to VC investments made in companies that have never received VC financing before. 'Follow-on round (VC)' refers to VC investments made in companies that have received VC financing before. 'Total (VC)' refers to the sum of 'first round (VC)' and 'follow-on round (VC)'. 'R&D' refers to privately-funded R&D expenditure. 'TFP growth' is the value-added weighted average of total factor productivity growth over 19 manufacturing industries. All others are sums of industry-level numbers.

Compared to the data used in Kortum and Lerner (2001), our VC investment figures are systematically large, even after taking into account the difference in constant dollar expressions.[12] This discrepancy probably occurs because Venture Economics backfills the older part of their database. The backfilling creates a survivorship bias such that a higher fraction of older data points is investment made by successful and surviving VC funds. As VC investment significantly increased in the late 1990s, and the recent investment, in the absence of backfilling, is likely to represent lower quality investment on average than in early periods, we might underestimate the effect of VC investment on innovations.

Table 2 shows VC investment tabulated by 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 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 the constant 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 absolute terms but also so in relative terms, representing 9.55% of the industry R&D expenditure. Notably, VC investment in Textile and Apparel is the second largest in relative terms, although it is small in absolute terms. In other industries, the relative presence of VC investments is quite small and often it is less than 1% 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 the average TFP growth in the Office and Computing Machines industry has is as much as 11.3%, indicating a positive correlation between innovation and VC investments. There is one caveat for interpreting this high number. One of the biggest obstacles in measuring innovation by TFP growth is the 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 analysis. In the 1980s, with the help of IBM, the Census Bureau measured quality change in the Office and Computing Machines industries. This is the only large-scale attempt made by the Bureau to incorporate quality improvement in analysis. For this reason, industries other than computer related industries might not exhibit substantial quality improvement in their TFP growth figures and their productivity growth rates might be underestimated.

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

*Table 2. Venture capital investments for US manufacturing industries, by industry (in millions of 2001 dollars)*

| | Industry | SIC codes | 1968–1969 | 1970–1974 | 1975–1979 | 1980–1984 | 1985–1989 | 1990–1994 | 1995–1999 | 2000–2001 | 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 |

Venture capital investments refer to the million dollar amount that venture capital funds invested in US companies of each industry and in each year.

*Table 3. Dollar amount (Panel A) and the ratio to privately-funded R&D expenditures of venture capital investments (Panel B), TFP growth (Panel C) and the number of patent applications (Panel D) for US manufacturing industries, by industry*

| | Industry | Mean | Median | Minimum | Maximum | Standard deviation |
|---|---|---|---|---|---|---|
| Panel A: Venture capital investment (in millions of 2001 dollars) | | | | | | |
| 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 | 2 890.29 | 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 | 3 902.99 | 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 | 9 530.68 | 1 855.40 |
| 16 | Other Electrical Equipment | 144.80 | 64.49 | 0.49 | 1 550.87 | 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 | 3 142.02 | 703.93 |
| Panel B: Venture capital investment/privately-funded R&D | | | | | | |
| 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*

| Industry | Mean | Median | Minimum | Maximum | Standard deviation |
|---|---|---|---|---|---|
| Panel C: TFP growth | | | | | |
| 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 | | | | | |
| 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 | 1324 |
| 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 | 3644 |
| 14 Other Non-electrical Machinery | 11 278 | 11 292 | 8 135 | 14 337 | 1769 |
| 15 Communication and Electronic | 4 558 | 2 952 | 2 403 | 11 274 | 2928 |
| 16 Other Electrical Equipment | 4 083 | 3 523 | 2 638 | 7 304 | 1466 |
| 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 | 3473 |

TFP growth for each industry is the value-added weighted average of the SIC four-digit level TFP growth.

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 the analysis of panel AR models, studying forecasting powers of VC investments and the two innovation measures. We begin by examining the relation between VC investment and TFP growth and then proceed to study the relation between VC investment and patent count. Unless stated otherwise, our sample period is from 1968 to 2001.

### 3.1. *Causality between VC investments and TFP growth*

We now present the model to be estimated and describe the results of our analysis on VC investment and TFP growth.

#### 3.1.1. *Panel AR models*

We borrow the idea of examining causality problems from Granger causality. The Granger causality test examines whether $X$ causes $Y$ by regressing $Y$ on the past realizations of $X$ and $Y$ and seeing whether the series of $X$ has any explanatory power. We apply this test to VC investment and TFP growth in panels. Let $X_{i,t}$ and $Y_{i,t}$ be TFP growth and the ratio of VC investment to privately-funded R&D expenditures in industry $i$ at time $t$, respectively. Our causality test consist of estimating the following equations:

$$X_{i,t} = \alpha_0 + \sum_{l=1}^{L} \alpha_l Y_{i,t-l} + \sum_{l=1}^{L} \beta_l X_{i,t-l} + \boldsymbol{\lambda}'\mathbf{Z}_{i,t} + \eta_i + \varepsilon_{i,t}, \text{ and} \tag{1}$$

$$Y_{i,t} = \gamma_0 + \sum_{l=1}^{L} \gamma_l X_{i,t-l} + \sum_{l=1}^{L} \delta_l Y_{i,t-l} + \boldsymbol{\psi}'\mathbf{Z}_{i,t} + v_i + u_{i,t}, \tag{2}$$

$$i = 1, \ldots, N, \; t = 1, \ldots, T,$$

where $L$ is the maximum lag length, $\eta_i$ and $v_i$ are unobserved industry-specific heterogeneities, $\mathbf{Z}_{i,t}$ is a set of control variables, and $\varepsilon_{i,t}$ and $u_{i,t}$ are idiosyncratic errors that may be contemporaneously correlated but are serially uncorrelated, conditional on $\mathbf{Z}_{i,t}$. In particular, we choose year dummies as the elements of $\mathbf{Z}_{i,t}$. We also assume $\eta_i$ and $v_i$ to be *fixed effects*, because if the industry effect represents omitted variables, it is highly likely that these industry-specific characteristics are correlated with the other regressors.

The nulls of 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 of first round investment and that of follow-on investment to privately-funded R&D expenditure. Two different lag scenarios are assumed: a 2-year lag and a 4-year lag. These time horizons are chosen based on the fact that firm start-ups have a realistic chance to grow typically 2–4 years after their initial VC investment.

We estimate the dynamic panel regression models (1) and (2) using two versions of the linear generalized method of moments (GMM) estimation and ordinary least squares (OLS) estimation. The first version of GMM is built on taking first differences of these equations ('difference GMM' by Holtz-Eakin *et al.*, 1988, and Arellano and Bond, 1991). To estimate equation (1) using the difference GMM, we impose the moment conditions:

$$E(X_{i,t-s}\Delta\varepsilon_{i,t}) = E(Y_{i,t-s}\Delta\varepsilon_{i,t}) = 0, t = 3, \ldots, T, s \geq 2, \tag{3}$$

as well as the conditions in which control variables are used as instruments. Replacing $\Delta\varepsilon_{i,t}$ with $\Delta u_{i,t}$ yields moment conditions for estimating (2). The second version of GMM imposes additional moment conditions as well as those implied by first-difference transformations ('system GMM' by Arellano and Bover, 1995, and Blundell and Bond, 1998). To equation (1) using the system GMM, in addition to equation (3), we make use of the moment conditions:

$$E(\varepsilon_{i,t}\Delta X_{i,t-1}) = E(\varepsilon_{i,t}\Delta Y_{i,t-1}) = 0, t = 3, \ldots, T. \tag{4}$$

Finally, the OLS-based estimation is referred to as the fixed effects within group or least squares dummy variable (LSDV) estimation, which transforms the data in deviations from the industry-specific means and runs OLS. We estimate equations (1) and (2) in three ways and check the robustness.[13] Moreover, for both difference and system GMM, we compute one-step estimators for inference.[14]

Table 4 and 5 present the estimation results for equations 1 and 2, respectively. While our main focus is to study two types of VC investment measures (the first and follow-on VC investments), we also provide results on the total VC investment (the sum of two measures), for reference. 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

[13] We estimate the models in three ways because both the time ($T = 34$, annually from 1968 to 2001) and industry dimensions ($N = 19$) of our panel data are small. To the best of our knowledge, there is no estimation strategy currently available that is well suited to the data. Both difference and system GMM estimators are designed for 'large $N$, small $T$' panels, whereas LSDV for 'large $T$, small $N$' panels. In addition, LSDV is known to yield biased estimates if the time dimension is modest. Judson and Owen (1999) show that biases may be substantial even when the time dimension is as large as 20–30.

[14] One-step estimators are often found to be more reliable than two-step estimators for inference purposes. See Arellano and Bond (1991), 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.

*Table 4. Testing for VC-first hypothesis on TFP growth*

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 | –0.0056 | –0.0095 | –0.0187 | –0.0252 |
| | (0.0325) | (0.0361) | (0.0258) | (0.0336) | (0.0436) | (0.0354) |
| First round VC/R&D(–2) | 0.1095*** | 0.1037** | 0.1053*** | 0.1225*** | 0.1150** | 0.1100*** |
| | (0.0419) | (0.0499) | (0.0367) | (0.0387) | (0.0500) | (0.0379) |
| First round VC/R&D(–3) | | | | –0.0639 | –0.0733* | –0.0421 |
| | | | | (0.0585) | (0.0402) | (0.0550) |
| First round VC/R&D(–4) | | | | –0.0268 | –0.0373 | 0.0118 |
| | | | | (0.0606) | (0.0577) | (0.0528) |
| TFP growth(–1) | 0.2616*** | 0.2467*** | 0.4973*** | 0.2321*** | 0.2303** | 0.4033*** |
| | (0.0786) | (0.0887) | (0.0707) | (0.0796) | (0.0900) | (0.0626) |
| TFP growth(–2) | –0.0500 | –0.0639 | 0.1716 | –0.0967 | –0.0972 | 0.0278 |
| | (0.0726) | (0.0811) | (0.1263) | (0.0705) | (0.0790) | (0.1158) |
| TFP growth(–3) | | | | 0.0205 | 0.0195 | 0.1486*** |
| | | | | (0.0732) | (0.0354) | (0.0359) |
| TFP growth(–4) | | | | 0.1213 | 0.1210 | 0.2635*** |
| | | | | (0.0874) | (0.0858) | (0.0642) |
| Arellano–Bond AR(1) test: *p*-value | | 0.01 | 0.01 | | 0.01 | 0.01 |
| Arellano–Bond AR(2) test: *p*-value | | 0.29 | 0.02 | | 0.50 | 0.37 |
| Sargan test: *p*-value | | 0.13 | 0.21 | | 0.34 | 0.31 |
| Granger causality test: | | | | | | |
| Wald statistic | 6.84 | 9.58 | 8.57 | 10.81 | 18.10 | 22.20 |
| *p*-value | (0.03) | (0.01) | (0.01) | (0.03) | (0.00) | (0.00) |

*Table 4. Continued*

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 | –0.0143 | –0.0510 | –0.0508* | –0.0512 |
| | (0.0408) | (0.0254) | (0.0518) | (0.0425) | (0.0288) | (0.0430) |
| Follow-on round VC/R&D(–2) | –0.0031 | –0.0077 | 0.1068 | 0.0011 | –0.0026 | 0.0449 |
| | (0.0594) | (0.0528) | (0.0828) | (0.0564) | (0.0577) | (0.0602) |
| Follow-on round VC/R&D(–3) | | | | –0.0266 | –0.0282 | 0.0506* |
| | | | | (0.0382) | (0.0281) | (0.0291) |
| Follow-on round VC/R&D(–4) | | | | –0.0467 | –0.0476 | 0.0436 |
| | | | | (0.0604) | (0.0676) | (0.0646) |
| TFP growth(–1) | 0.2650*** | 0.2575*** | 0.4928*** | 0.2348*** | 0.2329*** | 0.4015*** |
| | (0.0785) | (0.0844) | (0.0708) | (0.0791) | (0.0876) | (0.0614) |
| TFP growth(–2) | –0.0415 | –0.0479 | 0.1630 | –0.0879 | –0.0886 | 0.0296 |
| | (0.0733) | (0.0931) | (0.1271) | (0.0704) | (0.0828) | (0.1188) |
| TFP growth(–3) | | | | 0.0178 | 0.0167 | 0.1460*** |
| | | | | (0.0727) | (0.0322) | (0.0341) |
| TFP growth(–4) | | | | 0.1280 | 0.1268 | 0.2614*** |
| | | | | (0.0869) | (0.0837) | (0.0655) |
| Arellano–Bond AR(1) test: *p*-value | | 0.01 | 0.01 | | 0.01 | 0.01 |
| Arellano–Bond AR(2) test: *p*-value | | 0.22 | 0.02 | | 0.37 | 0.33 |
| Sargan test: *p*-value | | 0.06 | 0.10 | | 0.23 | 0.17 |
| Granger causality test: | | | | | | |
| Wald statistic | 0.91 | 3.05 | 4.03 | 3.61 | 4.68 | 3.22 |
| *p*-value | (0.63) | (0.22) | (0.13) | (0.46) | (0.32) | (0.52) |

*Table 4. Continued*

Dependent variable = TFP growth

| Independent variable | Lag = 2 LSDV | Lag = 2 D-GMM | Lag = 2 S-GMM | Lag = 4 LSDV | Lag = 4 D-GMM | Lag = 4 S-GMM |
|---|---|---|---|---|---|---|
| Total VC/R&D(–1) | –0.0281 | –0.0303* | –0.0117 | –0.0345 | –0.0370 | –0.0385 |
| | (0.0281) | (0.0181) | (0.0205) | (0.0290) | (0.0250) | (0.0280) |
| Total VC/R&D(–2) | 0.0474 | 0.0436 | 0.0785** | 0.0617 | 0.0574 | 0.0640* |
| | (0.0438) | (0.0424) | (0.0336) | (0.0448) | (0.0485) | (0.0356) |
| Total VC/R&D(–3) | | | | –0.0351 | –0.0389** | 0.0150 |
| | | | | (0.0288) | (0.0154) | (0.0260) |
| Total VC/R&D(–4) | | | | –0.0449 | –0.0480 | 0.0138 |
| | | | | (0.0407) | (0.0449) | (0.0384) |
| TFP growth(–1) | 0.2650*** | 0.2516*** | 0.4935*** | 0.2346*** | 0.2309*** | 0.4024*** |
| | (0.0784) | (0.0854) | (0.0715) | (0.0792) | (0.0887) | (0.0624) |
| TFP growth(–2) | –0.0459 | –0.0582 | 0.1643 | –0.0937 | –0.0955 | 0.0276 |
| | (0.0732) | (0.0888) | (0.1263) | (0.0709) | (0.0816) | (0.1176) |
| TFP growth(–3) | | | | 0.0187 | 0.0158 | 0.1460*** |
| | | | | (0.0729) | (0.0336) | (0.0347) |
| TFP growth(–4) | | | | 0.1266 | 0.1246 | 0.2629*** |
| | | | | (0.0866) | (0.0838) | (0.0651) |
| Arellano–Bond AR(1) test: *p*-value | | 0.01 | 0.01 | | 0.01 | 0.01 |
| Arellano–Bond AR(2) test: *p*-value | | 0.26 | 0.02 | | 0.48 | 0.40 |
| Sargan test: *p*-value | | 0.12 | 0.17 | | 0.35 | 0.26 |
| Granger causality test: | | | | | | |
| Wald statistic | 1.49 | 4.31 | 6.05 | 4.35 | 8.49 | 9.41 |
| *p*-value | (0.47) | (0.12) | (0.05) | (0.36) | (0.08) | (0.05) |

Does venture capital investment cause innovation? Dependent variables are TFP growth. Independent variables are lagged terms of various measures of VC investments and lagged TFP growth. The sample period is 1970–2001 ('Lags = 2') or 1972–2001 ('Lags = 4'). Results from least squares dummy variable ('LSDV'), one-step difference generalized method of moments (GMM) ('D-GMM') and one-step system GMM ('S-GMM') estimations are presented. Heteroskedasticity robust standard errors are in parentheses. Estimates with ***, ** and * are significant at the 1, 5 and 10% levels, respectively. Coefficients on time dummies are not reported. The null hypothesis for the Granger causality test is that all coefficients on VC investments are zero.

*Table 5. Testing for innovation-first hypothesis on TFP growth*

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 | 0.0874** | 0.0912*** | 0.0463 | 0.1516*** | 0.1131** |
| | (0.0294) | (0.0342) | (0.0252) | (0.0310) | (0.0479) | (0.0575) |
| TFP growth(–2) | 0.0250 | 0.0480 | 0.0189 | 0.0030 | –0.0207 | –0.0842 |
| | (0.0294) | (0.0916) | (0.0566) | (0.0272) | (0.0879) | (0.0757) |
| TFP growth(–3) | | | | 0.0778 | 0.2205 | 0.2281 |
| | | | | (0.0622) | (0.1784) | (0.1801) |
| TFP growth(–4) | | | | 0.0040 | 0.0018 | –0.1021 |
| | | | | (0.0686) | (0.1841) | (0.2097) |
| First round VC/R&D(–1) | 0.1465* | 0.0345 | 0.1998*** | 0.1410 | 0.0366 | 0.1783*** |
| | (0.0882) | (0.0452) | (0.0512) | (0.0911) | (0.0457) | (0.0299) |
| First round VC/R&D(–2) | 0.0915 | 0.0072 | 0.1654*** | 0.0902 | 0.0115 | 0.1240*** |
| | (0.0597) | (0.0177) | (0.0508) | (0.0617) | (0.0228) | (0.0459) |
| First round VC/R&D(–3) | | | | –0.0266 | –0.1301*** | 0.1596*** |
| | | | | (0.0877) | (0.0467) | (0.0417) |
| First round VC/R&D(–4) | | | | –0.0329 | –0.1309 | 0.1516 |
| | | | | (0.1070) | (0.1713) | (0.1559) |
| Arellano–Bond AR(1) test: *p*-value | | 0.17 | 0.16 | | 0.17 | 0.15 |
| Arellano–Bond AR(2) test: *p*-value | | 0.14 | 0.27 | | 0.13 | 0.21 |
| Sargan test: *p*-value | | 0.19 | 0.19 | | 0.10 | 0.15 |
| Granger causality test: | | | | | | |
| Wald statistic | 3.75 | 8.00 | 15.18 | 10.69 | 43.23 | 70.55 |
| *p*-value | (0.15) | (0.02) | (0.00) | (0.03) | (0.00) | (0.00) |

*Table 5. Continued*

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 | 0.2258 | 0.2962* | 0.0887 | 0.3047* | 0.2105* |
| | (0.0680) | (0.2130) | (0.1714) | (0.0622) | (0.1712) | (0.1152) |
| TFP growth(–2) | –0.0303 | –0.1082 | –0.1102* | –0.0569 | –0.1228 | –0.2534*** |
| | (0.0446) | (0.1003) | (0.0642) | (0.0450) | (0.0786) | (0.0848) |
| TFP growth(–3) | | | | 0.0623 | 0.1946** | 0.1855*** |
| | | | | (0.0584) | (0.0866) | (0.0680) |
| TFP growth(–4) | | | | 0.1412** | 0.3812** | 0.2303* |
| | | | | (0.0708) | (0.1877) | (0.1263) |
| Follow-on round VC/R&D(–1) | 0.6124*** | 0.5144*** | 0.6115*** | 0.5965*** | 0.4753*** | 0.5698*** |
| | (0.1931) | (0.1630) | (0.0982) | (0.1895) | (0.1301) | (0.0956) |
| Follow-on round VC/R&D(–2) | 0.0805 | –0.0119 | 0.2207 | 0.0610 | 0.0172 | 0.1480 |
| | (0.1517) | (0.1243) | (0.1403) | (0.1471) | (0.1063) | (0.1304) |
| Follow-on round VC/R&D(–3) | | | | 0.0219 | –0.0989 | 0.1365** |
| | | | | (0.0673) | (0.0691) | (0.0578) |
| Follow-on round VC/R&D(–4) | | | | 0.0364 | –0.0857 | 0.1446** |
| | | | | (0.0655) | (0.1010) | (0.0690) |
| Arellano–Bond AR(1) test: *p*-value | | 0.04 | 0.05 | | 0.03 | 0.03 |
| Arellano–Bond AR(2) test: *p*-value | | 0.77 | 0.01 | | 0.73 | 0.83 |
| Sargan test: *p*-value | | 0.09 | 0.05 | | 0.16 | 0.06 |
| Granger causality test: | | | | | | |
| Wald statistic | 2.17 | 6.63 | 4.17 | 8.62 | 25.89 | 44.84 |
| *p*-value | (0.34) | (0.04) | (0.12) | (0.07) | (0.00) | (0.00) |

*Table 5. Continued*

Dependent variable = Total VC/R&D

| Independent variable | Lag = 2 LSDV | Lag = 2 D-GMM | Lag = 2 S-GMM | Lag = 4 LSDV | Lag = 4 D-GMM | Lag = 4 S-GMM |
|---|---|---|---|---|---|---|
| TFP growth(–1) | 0.1343 | 0.3184 | 0.4060** | 0.1306 | 0.4551*** | 0.3426*** |
| | (0.0964) | (0.2335) | (0.1698) | (0.0893) | (0.1708) | (0.1018) |
| TFP growth(–2) | –0.0101 | –0.0898 | –0.0938 | –0.0620 | –0.1816 | –0.3435*** |
| | (0.0624) | (0.1899) | (0.1067) | (0.0618) | (0.1507) | (0.1032) |
| TFP growth(–3) | | | | 0.1372 | 0.4088** | 0.4141** |
| | | | | (0.0992) | (0.2003) | (0.2103) |
| TFP growth(–4) | | | | 0.1314 | 0.3503 | 0.1333 |
| | | | | (0.1216) | (0.3530) | (0.3056) |
| Total VC/R&D(–1) | 0.4292*** | 0.3326** | 0.4529*** | 0.4148*** | 0.3179*** | 0.4111*** |
| | (0.1477) | (0.1393) | (0.0966) | (0.1516) | (0.1084) | (0.0841) |
| Total VC/R&D(–2) | 0.2418** | 0.1735*** | 0.3308*** | 0.2586** | 0.2011*** | 0.2927*** |
| | (0.1179) | (0.0239) | (0.0690) | (0.1295) | (0.0305) | (0.0674) |
| Total VC/R&D(–3) | | | | 0.0321 | –0.1131 | 0.1762* |
| | | | | (0.1286) | (0.1190) | (0.1034) |
| Total VC/R&D(–4) | | | | –0.1103 | –0.2335* | 0.0315 |
| | | | | (0.1002) | (0.1305) | (0.1122) |
| Arellano–Bond AR(1) test: *p*-value | | 0.03 | 0.04 | | 0.03 | 0.04 |
| Arellano–Bond AR(2) test: *p*-value | | 0.38 | 0.93 | | 0.54 | 0.37 |
| Sargan test: *p*-value | | 0.15 | 0.14 | | 0.20 | 0.11 |
| Granger causality test: | | | | | | |
| Wald statistic | 1.94 | 6.09 | 6.96 | 10.34 | 66.11 | 74.64 |
| *p*-value | (0.38) | (0.05) | (0.03) | (0.04) | (0.00) | (0.00) |

Does innovation cause VC investment? Dependent variables are various measures of VC investments. Independent variables are lagged TFP growth and lagged terms of various measures of VC investments. The sample period is 1970–2001 ('Lags = 2') or 1972–2001 ('Lags = 4'). Results from least squares dummy variable ('LSDV'), one-step difference generalized method of moments (GMM) ('D-GMM') and one-step system GMM ('S-GMM') estimations are presented. Heteroskedasticity robust standard errors are in parentheses. Estimates with ***, ** and * are significant at the 1, 5 and 10% levels, respectively. Coefficients on time dummies are not reported. The null hypothesis for the Granger causality test is that all coefficients on TFP growth are zero.

equation (1), regardless of the VC investment measure or the lag length. The same test also rejects the null at the 5% level for equation (2) using the follow-on round and total VC investments. 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 equation (1) using the system GMM indicate a presence of second-order serial correlation, but this issue is resolved when the lag length is increased to four. Furthermore, most of the Sargan statistics provide little evidence of violating exogeneity in instruments.

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 AR terms are, in general, significantly positive, not surprisingly suggesting the presence of positive autocorrelation for both variables. An interesting observation is that in Table 5, estimated coefficients of the first-order AR 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.[15] 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 by examining the results of testing the null of no Granger causality from VC investment to TFP growth in Table 4. 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 2-year lagged VC investment. We can also see that coefficients on 1-year lagged VC investment tend to be negative (although insignificant at the 5% level). This suggests that VC investment is associated with a slowdown of TFP growth in the year following.

We now turn to Table 5, 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

[15] 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 5 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).

two-lag specification reject the null at the 5% level. In contrast, for the case of the follow-on investment, when the lag length is two, all Wald statistics other than the one from the difference GMM are so small as not to reject the null at the 5% level; even the one from the difference GMM fails to reject the null at the 1% 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 a maximum 2 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 is often reported. For both the first and the follow-on VC investment, the coefficients on 1-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 2 years, supporting the VC-first hypothesis. Nevertheless, both the first and the follow-on VC investment are negatively related with TFP growth in 1 year.

#### 3.1.2. *Industry analysis*

So far we have examined the relationship between TFP growth and VC investment using the panel AR analysis. The 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. Because 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 5 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 are 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 conduct the industry analysis, we introduce two new variables. First, we control for the industry capacity utilization when TFP growth is the dependent variable.[16] The construction of the TFP series assumes that capital is fully

[16] The data source for capacity utilization is the Federal Reserve Bank, Board of Governors. The capacity utilization data is classified by NAICS. We have matched with the KL code as follows (note that the numbers in the parentheses are associated with 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 a *p*-value of 0.01.

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 equation (2), we control for the policy changes that took place in 1979 and presumably stimulated the US VC industry. One of the changes concerns the supply side of VC investments. Before 1979, most pension funds had refrained from investing in VC so as not to violate the ERISA prudent man rule. 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 because each VC organization is typically small and does not have its own means of raising a large amount of funds directly from original investors. Another change is associated with the demand side of VC investments. In 1979, the highest marginal capital gains tax rate was reduced from 33.8 to 28%. Entrepreneurs backed by VC investments typically cash in on the firms that they have created by selling their stakes to third parties. These incomes are subject to capital gains tax. Thus, the reduction of the capital gains tax rate presumably encourages entrepreneurship and enhances the demand for VC investments. To control for the impact of this policy change on VC investment, we construct a dummy variable, the ERISA dummy, which takes a value of zero until 1979 and takes a value of one otherwise.[17]

Table 6 and 7 present the estimation results of the first and follow-on round VC investments as either dependent or independent variables, respectively. All regressions include 4-year symmetric lags of two variables and a quadratic time trend. Because the regressions are based on pure time-series data for individual industries, they are estimated using OLS. 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 AR 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 whether 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 the coefficients on lagged VC investments in this regression are significant. This result does not come as a surprise. In the Drugs industry, most technological innovations are improvements in the quality of drugs. Nevertheless, such improvement is difficult to measure and, therefore, it is unlikely that TFP growth is a good measure of innovation. Furthermore, drug development is a long process and, therefore, VC investments might have a positive impact on TFP growth after 4 years.

[17] 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.

*Table 6. Testing for VC-first hypothesis on TFP growth in selected industries*

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) |

*Table 6. Continued*

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) |

The sample period is 1972–2001. For each industry, the first and second columns display OLS results of the regression with a quadratic time trend and the regression with trends and a control variable 'CapUtil', respectively, as well as lagged VC investments and TFP growth. Heteroskedasticity robust standard errors are in parentheses. Estimates with ***, ** and * are significant at the 1, 5 and 10% levels, respectively. Constant terms and coefficients on autoregressive terms are not reported. The null hypothesis for the Granger causality test is that all coefficients on VC investments are zero.

*Table 7. Testing for innovation-first hypothesis on TFP growth in selected industries*

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) |
| $\text{Trend}^2$ | 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) |

*Table 7. Continued*

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) |

The sample period is 1972–2001. For each industry, the first and second columns display OLS results of the regression with a quadratic time trend and the regression with trends and a control variable 'ERISA', respectively, as well as lagged VC investments and TFP growth. Heteroskedasticity robust standard errors are in parentheses. Estimates with ***, ** and * are significant at the 1, 5 and 10% levels, respectively. Constant terms and coefficients on autoregressive terms are not reported. The null hypothesis for the Granger causality test is that all coefficients on TFP growth are zero.

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 1-year lagged TFP growth in both VC regressions are positive, consistent with the innovation-first hypothesis, whereas those on 1-year lagged VC investment in both TFP regressions are negative. One interpretation is that a rapid increase in VC investment is associated with a subsequent stock market crash and, therefore, recession (Abreu and Brunnermeier, 2003). TFP is positively related to macroeconomic conditions because manufacturing plants are more efficiently utilized in economic booms than during recessions and, therefore, if TFP growth slows down, recessions occur. Consistent with this explanation, the negative impact of VC on TFP growth no longer exists once capacity utilization is controlled for.

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 whether the first or the follow-on round VC investment is used. The coefficients on 1-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 4-year lagged TFP growth in VC regressions are consistent with the innovation-first hypothesis. A puzzling finding is that the estimated coefficients on 1–3-year lagged TFP growth in the follow-on VC regression are all negative.

This puzzling finding may reflect a life-cycle of innovation and industry. A typical life-cycle of an innovation is: generation of idea, creation of prototype, development of cost-effective manufacturing of the prototype (commercialization) and then adoption and learning by buyers of the innovation. VC investment is typically made during the commercialization stage of innovation. TFP growth occurs during the stage of adoption and learning. As in Jovanovic and Rob (1990), this life-cycle should be repeated due to marginally diminishing returns to each innovation. Therefore, if it takes 4 years from adoption and learning of one innovation to commercialization of the next innovation, we should observe the pattern that the 4-year lagged TFP growth has a significantly positive effect on VC investment but not other lagged TFP growth.

In the Other Electrical Equipment industry, we merely find that coefficients on the capacity utilization are significantly positive. There is little evidence of causality in either direction. However, similar to the results for the Office and Computing Machines industry, 1-year lagged VC investment in TFP regressions are negative and significant, and this significance disappears once capacity utilization is controlled for. These results are consistent with Abreu and Brunnermeier (2003).

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. However, 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 the validity of the innovation-first hypothesis at the entire manufacturing industry level. In particular, the significantly positive coefficients on 4-year lagged TFP growth in the follow-on VC equation appear to come from this industry's results. However, the same Communication and Electronic industry results provide supporting evidence that VC investment predicts a TFP growth slowdown in 1 year at the entire manufacturing industry level for the first round VC case.

## 3.2. *Causality between VC investments and patents*

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 subsections.

### 3.2.1. *Panel AR models*

We reestimate the panel AR models (1) and (2) by replacing TFP growth with the logarithm of patent counts, and perform the Granger causality test. The results in Table 8 and 9 correspond to those in Table 4 and 5, respectively. Again, the results on the total VC investment are provided for reference. All standard errors are based on the heteroskedasticity-robust formula. Overall, the estimated coefficients are robust across three different estimation methods. The coefficients on first-order AR terms are significantly positive. The results from the Arellano–Bond AR(2) test are acceptable in almost all cases. Moreover, most of the Sargan statistics do not indicate 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-first nor the innovation-first hypothesis is supported. Note that all coefficients on 1-year lagged VC investment and patent counts are positive but insignificant. However, for the case of the follow-on VC investment, the VC-first hypothesis is strongly supported over the 4-year time span. Nevertheless, the 1-year lagged follow-on VC investment is significantly and negatively related to patents, 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 is 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 the coefficients on lagged patent counts are significant at the 5% level (although they are positive in general).

*Table 8. Testing for VC-first hypothesis on patent*

Dependent variable = ln(Patent)

| Independent variable | Lag = 2 LSDV | Lag = 2 D-GMM | Lag = 2 S-GMM | Lag = 4 LSDV | Lag = 4 D-GMM | Lag = 4 S-GMM |
|---|---|---|---|---|---|---|
| First round VC/R&D(–1) | 0.0002 | –0.0005 | –0.0004 | 0.0001 | –0.0007 | –0.0009 |
| | (0.0011) | (0.0009) | (0.0008) | (0.0012) | (0.0010) | (0.0009) |
| First round VC/R&D(–2) | –0.0005 | –0.0002 | 0.0001 | –0.0004 | 0.0001 | 0.0005 |
| | (0.0013) | (0.0010) | (0.0011) | (0.0014) | (0.0010) | (0.0010) |
| First round VC/R&D(–3) | | | | –0.0004 | –0.0011 | 0.0014 |
| | | | | (0.0015) | (0.0013) | (0.0020) |
| First round VC/R&D(–4) | | | | –0.0015 | –0.0020 | –0.0034*** |
| | | | | (0.0016) | (0.0025) | (0.0016) |
| ln(Patent)(–1) | 0.9068**** | 0.8126**** | 0.9437**** | 0.9126**** | 0.8278**** | 0.9388**** |
| | (0.0900) | (0.1129) | (0.1816) | (0.0983) | (0.1070) | (0.1604) |
| ln(Patent)(–2) | 0.0687 | 0.0683 | 0.0595 | 0.1452*** | 0.2066**** | 0.1958**** |
| | (0.0825) | (0.1034) | (0.1835) | (0.0734) | (0.0428) | (0.0747) |
| ln(Patent)(–3) | | | | –0.0492 | –0.1321** | –0.0650 |
| | | | | (0.0754) | (0.0694) | (0.1083) |
| ln(Patent)(–4) | | | | –0.0481 | –0.0401 | –0.0712** |
| | | | | (0.0519) | (0.0671) | (0.0365) |
| Arellano–Bond AR(1) test: *p*-value | | 0.01 | 0.02 | | 0.02 | 0.04 |
| Arellano–Bond AR(2) test: *p*-value | | 0.11 | 0.08 | | 0.92 | 0.27 |
| Sargan test: *p*-value | | 0.06 | 0.15 | | 0.06 | 0.10 |
| Granger causality test: | | | | | | |
| Wald statistic | 0.16 | 0.28 | 0.41 | 1.01 | 1.86 | 5.18 |
| *p*-value | (0.93) | (0.87) | (0.81) | (0.91) | (0.76) | (0.27) |

*Table 8. Continued*

Dependent variable = ln(Patent)

| Independent variable | Lag = 2 LSDV | Lag = 2 D-GMM | Lag = 2 S-GMM | Lag = 4 LSDV | Lag = 4 D-GMM | Lag = 4 S-GMM |
|---|---|---|---|---|---|---|
| Follow-on round VC/R&D(–1) | –0.0066**** | –0.0043*** | –0.0059**** | –0.0041*** | –0.0039*** | –0.0060**** |
| | (0.0024) | (0.0020) | (0.0020) | (0.0017) | (0.0019) | (0.0019) |
| Follow-on round VC/R&D(–2) | 0.0052**** | –0.0003 | 0.0058*** | 0.0006 | 0.0000 | 0.0038 |
| | (0.0020) | (0.0010) | (0.0023) | (0.0015) | (0.0008) | (0.0026) |
| Follow-on round VC/R&D(–3) | | | | 0.0002 | –0.0014 | 0.0011 |
| | | | | (0.0011) | (0.0013) | (0.0013) |
| Follow-on round VC/R&D(–4) | | | | 0.0032**** | 0.0009 | 0.0029*** |
| | | | | (0.0012) | (0.0020) | (0.0012) |
| ln(Patent)(–1) | 0.9684**** | 0.7672**** | 0.9137**** | 0.8814**** | 0.7913**** | 0.8910**** |
| | (0.0910) | (0.0746) | (0.1597) | (0.0950) | (0.0788) | (0.1344) |
| ln(Patent)(–2) | 0.0445 | 0.1451**** | 0.0951 | 0.1671*** | 0.2164**** | 0.2223**** |
| | (0.0865) | (0.0562) | (0.1588) | (0.0692) | (0.0408) | (0.0595) |
| ln(Patent)(–3) | | | | –0.0281 | –0.1020** | –0.0210 |
| | | | | (0.0735) | (0.0561) | (0.0774) |
| ln(Patent)(–4) | | | | –0.0393 | –0.0057 | –0.0873 |
| | | | | (0.0466) | (0.0409) | (0.0552) |
| Arellano–Bond AR(1) test: *p*-value | | 0.01 | 0.02 | | 0.02 | 0.04 |
| Arellano–Bond AR(2) test: *p*-value | | 0.09 | 0.06 | | 0.50 | 0.30 |
| Sargan test: *p*-value | | 0.08 | 0.22 | | 0.07 | 0.14 |
| Granger causality test: | | | | | | |
| Wald statistic | 9.02 | 5.38 | 8.88 | 12.83 | 26.35 | 25.95 |
| *p*-value | (0.01) | (0.07) | (0.01) | (0.01) | (0.00) | (0.00) |

*Table 8. Continued*

Dependent variable = ln(Patent)

| | Lag = 2 | | | Lag = 4 | | |
|---|---|---|---|---|---|---|
| Independent variable | LSDV | D-GMM | S-GMM | LSDV | D-GMM | S-GMM |
| Total VC/R&D(–1) | –0.0015 | –0.0019 | –0.0017** | –0.0016 | –0.0017** | –0.0022*** |
| | (0.0010) | (0.0012) | (0.0009) | (0.0010) | (0.0010) | (0.0010) |
| Total VC/R&D(–2) | 0.0001 | –0.0003 | 0.0007 | –0.0003 | 0.0000 | 0.0003 |
| | (0.0008) | (0.0007) | (0.0005) | (0.0009) | (0.0004) | (0.0004) |
| Total VC/R&D(–3) | | | | 0.0005 | –0.0006 | 0.0015 |
| | | | | (0.0009) | (0.0010) | (0.0014) |
| Total VC/R&D(–4) | | | | 0.0014 | –0.0001 | 0.0008 |
| | | | | (0.0011) | (0.0018) | (0.0011) |
| ln(Patent)(–1) | 0.8892**** | 0.7800**** | 0.9205**** | 0.8948**** | 0.8016**** | 0.8972**** |
| | (0.0875) | (0.0871) | (0.1682) | (0.0962) | (0.0869) | (0.1398) |
| ln(Patent)(–2) | 0.0946 | 0.1135** | 0.0845 | 0.1615*** | 0.2247**** | 0.2314**** |
| | (0.0764) | (0.0682) | (0.1685) | (0.0710) | (0.0403) | (0.0580) |
| ln(Patent)(–3) | | | | –0.0449 | –0.1226*** | –0.0465 |
| | | | | (0.0739) | (0.0573) | (0.0889) |
| ln(Patent)(–4) | | | | –0.0436 | –0.0275 | –0.0810 |
| | | | | (0.0503) | (0.0513) | (0.0548) |
| Arellano–Bond AR(1) test: *p*-value | | 0.01 | 0.02 | | 0.02 | 0.05 |
| Arellano–Bond AR(2) test: *p*-value | | 0.06 | 0.06 | | 0.79 | 0.29 |
| Sargan test: *p*-value | | 0.07 | 0.19 | | 0.07 | 0.12 |
| Granger causality test: | | | | | | |
| Wald statistic | 2.19 | 5.18 | 5.48 | 3.57 | 9.66 | 12.99 |
| *p*-value | (0.33) | (0.07) | (0.06) | (0.47) | (0.05) | (0.01) |

Does VC investment cause innovation? Dependent variables are 'ln(Patent)', which is the logarithm of annual patent applications that were eventually granted. Independent variables are lagged terms of various measures of VC investments and lagged (logarithms of) patent counts. The sample period is 1970–2001 ('Lags = 2') or 1972–2001 ('Lags = 4'). Results from least squares dummy variable ('LSDV'), one-step difference generalized method of moments (GMM) ('D-GMM') and one-step system GMM ('S-GMM') estimations are presented. Heteroskedasticity robust standard errors are in parentheses. Estimates with ***, ** and * are significant at the 1, 5 and 10% levels, respectively. Coefficients on time dummies are not reported. The null hypothesis for the Granger causality test is that all coefficients on VC investments are zero.

*Table 9. Testing for innovation-first hypothesis on patent*

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 | 1.6864 | 2.5298 | 1.4261 | 1.5717 | 2.7052 |
| | (1.6753) | (2.5690) | (2.2141) | (1.8734) | (2.9836) | (2.4597) |
| ln(Patent)(−2) | −1.1110 | −1.4596 | −2.6897 | −0.1537 | 0.3248 | −0.6696 |
| | (2.7281) | (4.7755) | (2.4049) | (1.5240) | (1.7443) | (2.4237) |
| ln(Patent)(−3) | | | | −1.3392 | −2.3749 | −2.9670 |
| | | | | (2.1991) | (2.8384) | (2.7447) |
| ln(Patent)(−4) | | | | 0.3483 | 0.6336 | 0.7553 |
| | | | | (1.9480) | (2.9090) | (2.2267) |
| First round VC/R&D(−1) | 0.1535* | 0.1021* | 0.2347*** | 0.1487* | 0.1016* | 0.2118*** |
| | (0.0880) | (0.0522) | (0.0674) | (0.0880) | (0.0587) | (0.0558) |
| First round VC/R&D(−2) | 0.0941* | 0.0466* | 0.1634*** | 0.0968* | 0.0687*** | 0.1381*** |
| | (0.0561) | (0.0239) | (0.0507) | (0.0575) | (0.0218) | (0.0443) |
| First round VC/R&D(−3) | | | | −0.0285 | −0.1336*** | 0.1021*** |
| | | | | (0.0877) | (0.0454) | (0.0371) |
| First round VC/R&D(−4) | | | | −0.0326 | −0.1453 | 0.1099 |
| | | | | (0.1051) | (0.1330) | (0.1292) |
| Arellano–Bond AR(1) test: *p*-value | | 0.13 | 0.11 | | 0.14 | 0.11 |
| Arellano–Bond AR(2) test: *p*-value | | 0.19 | 0.33 | | 0.38 | 0.21 |
| Sargan test: *p*-value | | 0.13 | 0.15 | | 0.08 | 0.13 |
| Granger causality test: | | | | | | |
| Wald statistic | 2.77 | 2.34 | 1.35 | 3.39 | 5.94 | 5.64 |
| *p*-value | (0.25) | (0.31) | (0.51) | (0.49) | (0.20) | (0.23) |

*Table 9. Continued*

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 | 1.2198 | 3.7010 | 1.6728 | 1.0043 | 1.9276 |
| | (1.6217) | (2.3608) | (2.4883) | (1.7325) | (2.9844) | (1.7810) |
| ln(Patent)(–2) | 1.7671 | 3.6830 | –3.3726 | 1.7092 | 1.9526 | 4.6326 |
| | (2.0985) | (4.0550) | (2.4506) | (2.2427) | (2.1606) | (3.5658) |
| ln(Patent)(–3) | | | | –0.3670 | –0.0924 | –1.5467 |
| | | | | (2.4596) | (3.8092) | (3.6475) |
| ln(Patent)(–4) | | | | 0.8117 | 2.4435 | –4.8865 |
| | | | | (2.2774) | (2.5457) | (3.9357) |
| Follow-on round VC/R&D(–1) | 0.5438*** | 0.4987*** | 0.6528*** | 0.5383*** | 0.4928*** | 0.6228*** |
| | (0.1792) | (0.1263) | (0.1213) | (0.1792) | (0.1232) | (0.1286) |
| Follow-on round VC/R&D(–2) | 0.0636 | 0.0368 | 0.1951 | 0.0522 | 0.0343 | 0.1313 |
| | (0.1436) | (0.1384) | (0.1555) | (0.1451) | (0.1475) | (0.1638) |
| Follow-on round VC/R&D(–3) | | | | 0.0107 | –0.0132 | 0.1154** |
| | | | | (0.0652) | (0.0612) | (0.0557) |
| Follow-on round VC/R&D(–4) | | | | 0.0017 | –0.0183 | 0.1066 |
| | | | | (0.0586) | (0.0414) | (0.0720) |
| Arellano–Bond AR(1) test: *p*-value | | 0.03 | 0.04 | | 0.03 | 0.04 |
| Arellano–Bond AR(2) test: *p*-value | | 0.43 | 0.04 | | 0.45 | 0.59 |
| Sargan test: *p*-value | | 0.03 | 0.07 | | 0.02 | 0.05 |
| Granger causality test: | | | | | | |
| Wald statistic | 7.53 | 16.88 | 3.03 | 8.81 | 13.75 | 15.48 |
| *p*-value | (0.02) | (0.00) | (0.22) | (0.07) | (0.01) | (0.00) |

*Table 9. Continued*

Dependent variable = Total VC/R&D

| | Lag = 2 | | | Lag = 4 | | |
|---|---|---|---|---|---|---|
| Independent variable | LSDV | D-GMM | S-GMM | LSDV | D-GMM | S-GMM |
| ln(Patent)(–1) | 3.2467 | 2.9570 | 2.7926 | 3.3219 | 2.8175 | 2.7145 |
| | (2.6776) | (2.9367) | (17.0800) | (3.1160) | (3.8147) | (11.4254) |
| ln(Patent)(–2) | 1.1718 | 2.4108 | –0.6932 | 1.7549 | 1.5295 | –3.6150 |
| | (4.0949) | (5.5469) | (18.7135) | (2.8686) | (3.3141) | (13.6874) |
| ln(Patent)(–3) | | | | –2.1481 | –2.2345 | –0.4913 |
| | | | | (4.3696) | (4.9252) | (14.7628) |
| ln(Patent)(–4) | | | | 1.9858 | 3.5791 | 2.2229 |
| | | | | (3.8984) | (3.5582) | (7.8296) |
| Total VC/R&D(–1) | 0.3948*** | 0.3628*** | 0.7320*** | 0.3895*** | 0.3627*** | 0.3965*** |
| | (0.1288) | (0.0827) | (0.1080) | (0.1342) | (0.0753) | (0.1026) |
| Total VC/R&D(–2) | 0.2446*** | 0.2202*** | 0.0434 | 0.2762*** | 0.2648*** | 0.6144** |
| | (0.0944) | (0.0501) | (0.1584) | (0.1050) | (0.0558) | (0.2473) |
| Total VC/R&D(–3) | | | | 0.0114 | –0.0234 | 0.8464** |
| | | | | (0.1298) | (0.1205) | (0.4068) |
| Total VC/R&D(–4) | | | | –0.1459 | –0.1984*** | –0.2482 |
| | | | | (0.0924) | (0.0571) | (0.4295) |
| Arellano–Bond AR(1) test: *p*-value | | 0.04 | 0.14 | | 0.04 | 0.21 |
| Arellano–Bond AR(2) test: *p*-value | | 0.62 | 0.45 | | 0.83 | 0.73 |
| Sargan test: *p*-value | | 0.08 | 0.03 | | 0.06 | 0.01 |
| Granger causality test: | | | | | | |
| Wald statistic | 6.55 | 22.66 | 3.76 | 10.02 | 22.92 | 3.86 |
| *p*-value | (0.04) | (0.00) | (0.15) | (0.04) | (0.00) | (0.43) |

Does innovation cause VC investment? Dependent variables are various measures of VC investments. Independent variables are lagged (logarithms of) patent applications that were eventually granted and lagged terms of various measures of VC investments. The sample period is 1970–2001 ('Lags = 2') or 1972–2001 ('Lags = 4'). Results from least squares dummy variable ('LSDV'), one-step difference generalized method of moments (GMM) ('D-GMM') and one-step system GMM ('S-GMM') estimations are presented. Heteroskedasticity robust standard errors are in parentheses. Estimates with ***, ** and * are significant at the 1, 5 and 10% levels, respectively. Coefficients on time dummies are not reported. The null hypothesis for the Granger causality test is that all coefficients on (logarithms of) patent counts are zero.

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 4-year horizon. However, the negative impact of the follow-on round VC investment on patent count casts doubt on the validity of the VC-first hypothesis.

3.2.2. *Industry analysis*

For the same 5 industries as used in Section 3.1.2., we run VC and patent regressions. As before, all the regressions are estimated using OLS. 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 to patent policies in the early 1980s; namely, the introduction of the Bayh–Dole Act in 1980 and the establishment of the 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 a dummy variable, D1981, which takes a value of zero until 1980 and takes a value of one otherwise.[18]

Table 10 and 11 present the estimation results of the first and follow-on round VC investments as either dependent or independent variables, respectively. Again, all regressions include 4-year symmetric lags of two variables and 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 AR 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 whether 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; in fact, in 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 1-year lagged VC investment contribute 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 10. 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 1-year lagged patent counts for the follow-on VC case in the Professional and Scientific Instruments industry.

[18] The correlation coefficient between patent counts and D1981 is 0.13, with a $p$-value of 0.00.

*Table 10. Testing for VC-first hypothesis on patent in selected industries*

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) |

*Table 10. Continued*

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) |

The sample period is 1972–2001. For each industry, the first and second columns display OLS results of the regression with a quadratic time trend and the regression with trends and a control variable 'D1981', respectively, as well as lagged VC investments and lagged (logarithms of) patent counts. Heteroskedasticity robust standard errors are in parentheses. Estimates with ***, ** and * are significant at the 1, 5 and 10% levels, respectively. Constant terms and coefficients on autoregressive terms are not reported. The null hypothesis for the Granger causality test is that all coefficients on VC investments are zero.

*Table 11. Testing for innovation-first hypothesis on patent in selected industries*

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) |

*Table 11. Continued*

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) |

The sample period is 1972–2001. For each industry, the first and second columns display OLS results of the regression with a quadratic time trend and the regression with trends and a control variable 'ERISA', respectively, as well as lagged VC investments and lagged (logarithms of) patent counts. Heteroskedasticity robust standard errors are in parentheses. Estimates with ***, ** and * are significant at the 1, 5 and 10% levels, respectively. Constant terms and coefficients on autoregressive terms are not reported. The null hypothesis for the Granger causality test is that all coefficients on (logarithms of) patent counts are zero.

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 1 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 'funds available for VC investment' as an explanatory variable for VC investment; see the Appendix for an explanation of how to construct the variable 'funds available for VC investment'. Testing results are qualitatively similar to those reported in this section.

## 4. CONCLUDING REMARKS

This paper has examined both directions of the causality between innovation and VC investment using a framework similar to the Granger causality test. For this purpose, we studied a panel of US 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, 1-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 for 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 1 year later at individual industry levels. This result is consistent with Engel and Keilbach (2007) and Caselli *et al.* (2009), who find significant slowdown of patenting activities once patenting firms obtain VC funding.

These results suggest that the time-series relation between VC investment and innovation 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. We often find that VC investment leads to a slowdown in TFP growth and patenting activity.

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## APPENDIX: CONSTRUCTION OF 'FUNDS AVAILABLE' 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: typically, every 2–5 years. Therefore, 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 'funds available'. Here, we describe how we constructed this dataset.

VentureXpert provides the amount of funds raised most of the time. However, the amount of funds that were actually disbursed is not well recorded. If it is recorded, the total syndicated amount of disbursement is recorded but the individual contribution amount 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 5 years as the disbursement life. Some funds have establishment years but no investment history recorded. For such funds, we simply set their disbursement life equal to 5, and thus we 'assign' 5 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 (specifically, fitting ARIMA(2,1,2) to the logarithm of VC disbursements). 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, therefore, 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, therefore, no portfolio companies. For these funds, we assume that they have no particular industrial preferences. Then, for each such fund we allocate available capital in each year over all industries disbursed in the year by using actual disbursements as weights. 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 years during the disbursement life.

To construct the funds available in the way described above, we examine all VC funds that were established from 1960 to 2002 and focus on investing in the US companies. We drop those without fund size data from our sample. The funds eliminated in this screening are typically those established before the mid-1980s, 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. We also eliminate the funds that have a fund size but neither an establishment year nor an investment history. Then, in the final step, we obtain the KL-classified funds available data in constant dollars by aggregating all available capital over each KL classification in each year and deflating it.