Venture Capital Investment and Creative Destruction

Wei Wang

Cleveland State University
w.wang24@csuohio.edu

Chris Yung
University of Virginia
cay2m@comm.virginia.edu

Abstract

VC investment in a given Fama-French 49 industry is associated with future creative destruction among public incumbents in the same industry as measured by firm mobility across industry rankings. By contrast, R&D spending by incumbents has no relation (or even negative relation) with industry-level creative destruction. This is consistent with Schumpeter's hypothesis that creative destruction owes to small entrepreneurial firms, whereas R&D proxies for investment by entrenched firms refining existing technologies rather than disrupting the status quo. We exploit exogenous regulatory events in order to establish causality and conclude that only efficient VC investment leads to creative destruction.

Keywords: Firm mobility, venture capital, creative destruction, innovation

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1. Introduction

Personal income (or wealth) mobility is viewed as a desirable property of an economy. An individual's ability to move upward suggests freedom of opportunity. Aghion et al. (2019a) equate economic mobility with innovation because entrepreneurs who create successful businesses become wealthy. Lack of mobility – i.e., the maintenance of status quo – indicates lack of economic dynamism.

In this paper we adopt a similar view at the firm level. Periods of creative destruction are marked by the introduction of new technologies which determine winners and losers. Winners include the innovators themselves and those poised to benefit indirectly from the disruption. Losers are those who employ outdated technology and those who fail to adapt to new modes of doing business. To measure mobility, we track firm rank permutation, namely, movement over time in rankings within an industry, interpreting times of heightened mobility as periods of creative destruction.

It is natural to ask what factors are associated with creative destruction. This paper focuses on industry-year-level venture capital (VC) investment. Schumpeter (1912) and others[1] argue that disruptive innovations tend to originate in small entrepreneurial firms. The VC profession has evolved to serve this niche, and is tailored for investments deemed too risky or uncertain for banks – and therefore particularly likely to be disruptive.

In our main test we examine the association between i) aggregate VC investment in a Fama-French 49 industry over rolling five year periods and ii) firm rank permutation among publicly traded industry firms in that same industry over *subsequent* periods.

<u>Creative Destruction Effect</u>: *Aggregate VC investment in an industry is positively associated with subsequent firm mobility among public incumbents in the same industry.*

Our firm mobility measure is defined as follows. Within each year and each Fama-French 49 industry, we rank firms by sales. We convert this ranking to a percentile and record each firm's change in percentile over a five-year window. For each industry and each rolling five-year

[1] Aghion, Akcit and Howitt (2014) summarize "Freeman (1982), Pennings and Buitendam (1987), Tushman and Anderson (1986), Scherer (1984) and Akcigit and Kerr (2018) show that large incumbents focus on improving existing technologies whereas small new entrants focus on innovating with new radical products or technologies". Evidence in Hellman and Puri (2000) is consistent with VC-backed firms pursuing disruptive product market strategies.

window, we compute the standard deviation across all firms in the industry. This cross-sectional second-moment estimate becomes our main industry-level measure of firm mobility which we call *rank permutation*. We perform similar exercises using year-end assets and market capitalization. Unlike sales and assets, market capitalization is a forward-looking metric of firm size. As such, we measure the rank permutation over a one-year window. Additionally, emphasizing the *destructive* part of creative destruction – we document the propensity of firms to delist (*firm exit*), and the propensity of top firms to exit the top decile (*leader turnover*).

Our results are consistent with the creative destruction effect. We find a strong positive association between VC investment and future public firm mobility in an industry during 1975-2011, regardless of the measure of firm size on which rank permutation is based. These relations remain after controlling for industry characteristics, including industry market-to-book ratio as a (probably imperfect) proxy of technological opportunities, as well as fixed industry and year effects. Statistical and economic significance of these relations is generally substantial. In general, doubling VC investment in an industry would lead to an increase in subsequent firm rank permutation by roughly 10 percent of the average rank permutation.

We next address the question of causality. Even if VC investment is associated with future creative destruction, the association need not be causal. It could instead reflect an omitted variable. For example, both venture investment and future creative destruction could stem from unobserved investment opportunities even if VC firms are themselves were responsible for a negligible part of the destruction.[2] The causality investigation answers such a question: holding investment opportunities constant, will variations in VC investment lead to differences in creative destruction?

To address causality, we borrow two approaches from Kortum and Lerner (2000) who face a similar omitted variable problem. First, other than controlling for industry market-to-book ratio, we also employ R&D as a "control" in a variety of ways. R&D expenditures are affected by a similar omitted variable as described above. In particular, R&D expenditures reflect the response of market participants to variables which they observe – i.e., it acts as a proxy for investment opportunities which are not directly observed by econometricians.

[2] If policymakers are interested in predicting creative destruction, then documenting such a statistical relation is useful even without causality, i.e., if VC investment waves act as a public signal of an omitted variable which is privately observed by market participants but (by definition) not observed by econometricians.

Second, we use a quasi-natural experiment provided by the passage of ERISA. This regulatory shift allowed institutional investors greater leeway to invest in private equity as limited partners. Consequently ERISA reflects an exogenous, one-time increase to the supply of VC funds relative to other capital suppliers while affecting neither the investment opportunity set nor the demand for capital.

The idea behind this test is as follows. It is possible that VCs simply respond to opportunities for creative destruction, but are no better at causing it than other financiers. Alternatively, it is possible that VCs excel at causing creative destruction when the possibilities are present. If the latter holds, then we should observe a break in the amount of creative destruction occurring at the point when supply constraints were relaxed. Furthermore, we conduct a difference-in-difference test comparing the outcomes in high market-to-book and low market-to-book industries where VC supply is less relevant consideration. Our results are consistent with a causal interpretation.

We replicate our ERISA analysis with another regulatory shock. NSMIA passed in 1996 exempts private 506D offerings from the effect of "blue sky laws" at the state level. Previously, a private firm wishing to sell these unregistered securities to individuals in multiple different states had to comply with the blue sky laws in each state, which is burdensome (Ewens and Farre-Mensa, 2019). Unlike with ERISA, we find little or no difference in the pre- and post-NSMIA samples. One possible explanation for this finding is that by the late 1990s, VC investment was no longer significantly supply-constrained.

Our next test is motivated by the fact that creative destruction can extend beyond an industry's borders. An innovation may allow firms to outcompete firms in neighboring industries, e.g., developments in shale oil technology affect those who produce or transport coal. Alternatively an innovation may have effects along a supply chain, creating winners and losers within downstream or upstream industries. To investigate these spillovers, we consider each Fama-French 49 industry and define a "neighboring" industry as the industry with the highest raw correlation in industry stock returns. We then perform a similar test, i.e., we examine whether aggregate VC investment in a particular Fama-French 49 industry is associated with firm rank permutation among public incumbents in neighboring industries. We hypothesize:

<u>Spillover Effect</u>: *Aggregate VC investment in an industry is positively associated with subsequent creative destruction among public incumbents in neighboring industries.*

Our results are generally consistent with the spillover effect. VC investment is a given industry is associated with creative destruction in neighboring industries, albeit at reduced magnitude compared to the home industry.

1.1 Related Literature

1.1.1 Papers Focusing on Determinants of R&D or Patenting

One strand of related literature examines the determinants of R&D and/or patents, generally viewing R&D as an input of innovation and patents as the output (e.g., Acharya and Subramanian, 2009; Aghion et al., 2013; Brav et al., 2018). This literature shares with our paper a common overall interest in what factors drive innovation.

Compared with this literature, our approach offers both advantages and disadvantages. First, R&D data are available only for public firms whereas under Schumpeter's view creative destruction may originate in small private firms. Second, patenting and innovation are correlated phenomena but they are not identical. Many innovations are non-patented[3] and many patents are non-innovative.[4] By contrast, our firm mobility measures are designed to document the actual operating effects of an innovation on industry participants. However, a limitation of our approach is that we cannot generate firm-level impact measures (unlike the patent literature). In particular when we observe a spike in industry-level firm mobility, we cannot attribute it to any particular firm's actions. Rather, we can only document which industry-year characteristics are associated with creative destruction.

Mina, Lahr and Hughes (2013) find that more innovative firms (as measured by patenting activity) tend to by externally financed. Acharya and Xu (2017) show that external finance is associated with higher quality patents and more innovative patents. The role of capital market

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[3] Fontana, Nuvolari, Shimizu and Vezzulli (2013?) survey historical evidence and conclude that the most impactful innovations (as defined by industry experts) are often unpatented. Hall and Zedonis (2001) and Moser (2005, 2012) conclude similarly.

[4] Shapiro (2001) laments that patenting in the modern era too often covers "products or processes already being widely used when the patent is issued, making it harder for the companies actually building businesses and manufacturing products to invent around these patents". He opines that, rather than acting as proxy for innovation, modern patenting is a legal arms race.

quality is further codified by Moshirian, Tian, Zhang and Zhang (2020) and Hsu, Tian and Xu (2014), who together show cross-sectional and time-series evidence that finance stimulates patent production. These papers share with us a focus on innovation. The approaches differ from ours in i) the dependent variable employed and ii) our narrow focus on venture capital.

Our paper is closely related to Kortum and Lerner (2000) who compare the effects of venture funding with that of R&D in the patent production process. Kortum and Lerner find that VC funding leads to more patents and higher quality patents. Our methodology is informed by their choices (see Section 3.5) although we study firm mobility rather than patents.

Kortum and Lerner's (2000) result can be juxtaposed against research examining the effects of VC on total factor productivity. Ueda and Hirukawa (2008) find that at the industry level, venture investments are associated with patent propensity, yet this patenting differential does not translate into productive efficiency as measured by TFP. The results together suggest a curious disconnect in which VCs apparently produce innovation (as defined by patents) without commensurate real effects.

This discrepancy may be partially reconciled by Aghion et al.(2019b) who argue that creative destruction causes economists to mismeasure TFP. Creative destruction implies that some products disappear. Economists generally have approached this issue using imputation (based on surviving products) yet Aghion et al. point out that doing so systematically involves a mismatch. In particular, the "destroyed" products have a different inflation than surviving products, causing TFP growth to be substantially underestimated. Aghion et al. estimate that "almost of the missing growth is due to creative destruction".

Surveying this literature, Da Rin, Hellman and Puri (2013) find the apparent mismatch between patents and TFP results "surprising" and conclude "these papers highlight the difficulties of identifying the relationship between VC and innovation at the industry level".

The literature's limited ability to document any real (non-patenting) effects of innovation by venture capital funded firms provides the proximate motivation for the current study.

1.1.2 Papers Focusing on Creative Destruction

Another branch of literature is closely related methodologically to our paper but less related topically than the papers summarized in Section 1.1.1. These papers employ firm mobility measures (and, like us, may interpret them in terms of creative destruction) but may use them for other purposes. For example, creative destruction acts as an *independent* variable in order to explain macroeconomic growth. These papers are described below.

Fogel, Morck and Yeung (2008) find that national economies tend to grow slowly if they are composed of entrenched large businesses. These businesses are positively associated with government spending, regulatory barriers to entry, bank-centered financial systems, weak outside shareholder protection, and trade barriers. Fogel et al. define "big business stability" as fraction of large companies at T who are still surviving at $T+t$. Our exit rate and leader turnover measures are similarly defined, although we employ them as dependent variables rather than independent variables. The picture painted by Fogel et al. is that stable large businesses are detrimental to growth. Our research contributes to this line of thinking by examining the extent to which VC financing hastens turnover of large firms.

Closer to our study are Brown, Fazzari and Peterson (2009) and Brown and Peterson (2010). While these papers examine the link between R&D and external finance, Brown and Peterson document an intriguing creative destruction result. They examine the real effect of IPOs on incumbents within six high-tech industries. They find that in industries with the most active IPO markets, incumbents subsequently lose market share. This link between finance and real outcomes is shared with our paper. However, our focus is one step earlier in the lifecycle (at private investments rather than public equity) as well as broader (all industries with a time series of venture capital investment).

Chun, Kim, Morck and Yeung (2008) investigate how adoption of information technology creates heterogeneity in sales growth and stock returns among firms, and interpret it as evidence of creative construction. Their main dependent variable is an adjusted sum of squared residuals at the firm level from a regression of firm performance on market and industry performance.

Liang, McLean and Zhao (2013) also use creative destruction as a dependent variable. Their independent variable of interest is a measure of the overall quality of US capital markets. In particular, they examine whether improvements in capital market quality lead to turnover of leading businesses, the entry/exit of firms, and variation in growth rates. Their argument is as follows. Small firms are more dependent on external capital markets than large firms, which can instead utilize internal financing. Capital markets enable small firms to better compete against large firms and therefore facilitate creative destruction. Our focus is on the level of VC investment, and this difference offers both advantages and disadvantages. The disadvantage is that our approach limits us to a narrower question compared to Liang et al. (2013) who examine the broader role of capital markets. One advantage of our independent variable is that it can be defined at the industry level so as to align closely with our dependent variable, i.e., we document how private investment in a given industry leads to real changes in that same industry.

2 Data and Measurement Issues

Our initial source of venture data is the Thompson Reuters VentureXpert database. For every portfolio firm and for every round, we record the total amount of capital raised in the round, the date of the round, and the company's primary SIC code. We restrict attention to US-based firms and screen out the following transactions: 1) private investments in public equity (PIPE), leveraged buyouts (LBO), and others classified as "public market" transactions, 2) transactions made by funds of funds, 3) financial, banking, insurance and real estate companies, 4) utilities firms, and 5) companies that are 15 years old or older. We also manually excluded several misclassified buyout and M&A transactions. Our initial sample consists of 114,364 rounds of finance which cover 40,135 distinct firms in 44 Fama-French 49 industries during 1971-2016.

From Compustat and CRSP we extract financial data and delisting information (if any). While constructing firm mobility variables, we exclude firms that change their industries during our sample period.

2.1 Measures of VC Activity

We organize the VentureXpert data as follows. For each Fama-French 49 industry and each year, we sum the total dollar value of capital invested in that industry during the preceding five-year period (including the observation year), and take logarithm of one plus the value to mitigate skewness. VC investments are adjusted by consumer price index to the dollar value in year 2000 and expressed in million dollars.

2.2 Measures of firm mobility within an industry

Benchmarking is critical for our research question. If creative destruction in a given area creates winners and losers within the industry, then we should measure relative performance rather than absolute performance. Alternatively, for example an industry could be in overall decline (say due to decreased demand) but without new technology shifts and thus without relative winners or losers. Under with view, we define the following measures.

Rank permutation. Our main measure of firm mobility is rank permutation. For each industry-year with at least five firms, we rank all firms by size. Each firm is then assigned a rank within the industry, which is then normalized to the (0, 1] range. For example, if an industry has 10 firms in a year, then the rank values are 0.1, 0.2, …., 0.9, and 1. For each firm, we identify its rank change over a N-year period. In the baseline definition, if a firm is delisted, we set its rank value to 1 after the delisting year. For each N-year period we calculate the standard deviation of rank change across all firms in the industry. We perform this exercise separately using three proxies for firm size: annual sales, total assets at the end of calendar year, and market capitalization at the end of calendar year. For sales and assets, N is set to five; that is, we mainly examine the rank permutation over a five-year period following VC investments in the preceding five-year period. Market capitalization is already a forward-looking metric, and as such, we consider the one-year period rather than five-year periods. In short, for an industry in year t, we measure venture capital investment based on data in years t-4 to t, and create the measures of firm mobility based on data in years t+1 to t+5 (for sales and assets) or in year t+1 (for market capitalization).

Creative destruction may also have effects at the two tails of the firm distribution within an industry. Thus, we also consider corporate exits (the left tail) and leader turnover (the right tail).

Corporate exits. In an extreme case of creative destruction, a firm must exit the market. We measure corporate exits by both the number of delisting and the rate of delisting in a five-year period in an industry.

Leader turnover. Liang et al. (2013) describe an extreme case of creative destruction in which business leaders lose their leading positions. We define leader turnover as the fraction of top decile firms within a Fama-French 49 industry that drop out of the top decile in the subsequent period. Ranking of firms again are based on sales, total assets, and market capitalization, respectively. The length of subsequent period is five years for sales and assets, and one year for market capitalization. To avoid integer-related artifacts[5] when using this measure we consider only industry-years that begin with 50 or more companies at the observational year.

2.3 Mergers and acquisitions

Treatment of acquisitions involves a judgement call. Our mobility measures are directly affected by M&A activity[6] since a merger involves the delisting of one firm and the growth of another. On the one hand, a period of unusual structural change within an industry can represent a response to an emerging threat. For example, the rapid growth of AirBnB, Priceline and Booking.com preceded a merger wave among traditional hotel chains (Marriott-Starwood, Accor-Fairmont, Windham-Dolce, etc.) This argument favors leaving acquisitions in our sample. On the other hand, creative destruction has non-M&A implications for organic growth and decline of non-merging firms. We would like to examine these effects as well.

Based on this view, we report our results in two separate ways. First, we treat acquiring firms just like any other firm with its rank change, and (if applicable) leading position calculated similarly. Delisting firms are considered to have moved to the bottom of the industry. In an alternative specification, we take two steps to purge the effect of mergers. First, if CRSP lists the reason for delisting as acquisition, we set the value of rank change and exits as missing. Second, to mitigate the effect on acquirers (and especially because some acquisitions are private) we flag any firm with assets of at least 200 million dollars[7], in any year in which the growth rate of assets exceeds 50%. These firms are then excluded from the rank permutation for the five preceding years.

2.4 Control variables

We control for other factors likely to affect firm mobility. The first control variable is *industry R&D* expenses. We aggregate the R&D expenses of COMPUSTAT firms within each industry-year, and then sum over rolling five year windows. To mitigate skewness, we employ the logarithm of this value. R&D expenses by incumbents have mixed implications for firm mobility.

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[5] For example, an industry with N=30 has three leaders, whereas an industry with N=29 has just two leaders (both of whom are in a relatively strong position).

[6] To be clear, our mobility measures are affected by periods with atypical levels of M&A activity. During periods with typical levels of M&A activity, our mobility measures will be at normal levels.

[7] Organic growth of over 50% is not rare among small firms. The median value of assets in our sample is 237 million dollars.

On the one hand, Schumpeter (1942) emphasizes that for incumbents to invest in innovation they require the expectation of continued monopoly power. Thus R&D expenditures are likely concentrated among incumbents who have erected the strongest barriers to entry. Any resulting innovations must therefore be – according to our definition – non-disruptive because the investments are undertaken by entrenched incumbents. On the other hand, as incumbent companies have discrepant capabilities to capitalize technological opportunities, heightened R&D investments in an industry would lead to varying growth and greater firm mobility. In other words, disruptive and non-disruptive effects might co-exist for incumbents' R&D expenses. Hence the net effect of industry R&D is an empirical issue.

Industries which have more dominant firms may be more resistant to change, and hence we control for industry Herfindahl-Hirschman index *(industry HHI)*, calculated based on sales, assets, and market capitalization, respectively. If an industry has a lot of large firms, the bar for creative disruption may be higher. For this reason, we control for *industry firm size* as the average logged firm size, that is, sales, assets and market capitalization, respectively, in an industry at the observational year t. The size dispersion of firms in an industry (*firm size dispersion*) may have implications for firm mobility: widely-dispersed firms may be at the different stages of their lifetime and exhibit greater variation in growth, but at the same time it takes greater disruptions to cause a change in rank. Thus its net effect is an empirical issue. We use the logarithm of standard deviation of firm size, again measured by sales, assets and market capitalization, to proxy for industry dispersion.

As one may argue that technological opportunities are the ultimate source of firm mobility, we attempt to control for the arrival of technological opportunities using *industry market-to-book* ratio. Controlling this factor would allow us to highlight the net effect of VC investment: holding technological opportunities constant, how variations in VC investment, e.g., underinvestment or overinvestment, would affect subsequent firm mobility?

More industry characteristics to consider include *industry leverage* and *liquidity*. An industry's leverage and liquidity might affect firm performance variation. For instance, higher leverage enhances market capitalization volatility, and cash reserves help firms weather ill times without sacrificing key assets. Following Chun et al. (2008), we measure the former the total debt-to-total asset ratio and the latter total current assets over total current liabilities for an industry in each year. In addition, we use fixed industry effects to control for unobservable, time-invariant industry characteristics.

Firm rank permutation among publicly listed firms could be generated by new entry firms, namely IPOs. We thus control for industry *IPO intensity*, measured as the total number of IPOs in an industry during the preceding five-year period as a ratio of total number of public firms in the industry at the observational year t.

Macroeconomic conditions such as GDP growth, inflation and interest rates might contribute to varying firm mobility over time. Liang et al. (2013) document that firms are likely to exhibit greater variation in growth rate and leader turnover in certain financial market conditions. We control for these factors using year dummies to focus on firm mobility at the industry level.

2.5 Summary Statistics

Appendix A defines the variables used in this study. Table 1 presents the descriptive summary of these variables. Although we have VC investment values for all the 1,628 industry years, the number of observations varies for different measures of firm mobility, depending on data availability. On average, an industry-year features VC investments totaling 1.26 billion dollars. VC activities vary widely, ranging from none for some industry-years to nearly 20 billion dollars for some others. Rank permutation averages 0.25 based on sales and assets over the five-year horizon and 0.13 based on market capitalization over the one-year horizon. On average we observe about 19 firms exiting in an industry during a five-year period, and the average five-year exit rate is 23 percent. Out of the top decile firms measured by sales or assets (market capitalization) in an industry in a year, approximately 30 (15) percent of them drop out of the top decile in the subsequent five-year (one-year) period. Our data therefore features substantial within-industry mobility.

During any five-year period, firms in an industry on average spend 13 billion dollars in R&D and it varies widely across industries, with the 1st percentile being 0 and the 99th percentile being 146 billion dollars. The average HHI for sales, assets, and market capitalization are 0.16, 0.17, and 0.18, respectively, and the logged firm size averages about 6.9 with a standard deviation of around 7.6, regardless of the measure of firm size. Average industry leverage ratio is 0.27 and liquidity ratio is 1.16, both with considerable variations across industries. IPO intensity also varies a lot, being zero at the 1st percentile and 1.2 at the 99th percentile. The average is 0.28, indicating that for an industry of 100 firms at year t, on average 28 firms were taken public in the preceding five years.

[Table 1 about here]

3 Results

3.1 Univariate analysis

We first sort our sample by the level of VC activity in each industry-year. Out of the 1,628 industry-years, we classify the top quartile as "High", the bottom quartile as "Low", and the middle half as "Intermediate" in VC investments. We compare firm rank permutation across these categories. Results are reported in Table 2.

Corporate rank permutation increases monotonically with VC investments. The standard deviation of sales rank change is 0.233, 0.245, and 0.282 in the Low, Intermediate, and High VC categories, with the difference between High and Low categories statistically significant at the one percent level. Rank permutations based on assets and market capitalization exhibit similar patterns.

[Table 2 about here]

3.2 Multivariate analysis

Our multivariate analysis estimates the determinants of firm mobility measures using VC investments as the key independent variable with industry and macroeconomic conditions as control variables. The baseline model specification is as follows:

$$Mobility_{i,[t+1,t+5]} = \alpha_i + \theta_t + \beta \cdot VC_{i,[t-4,t]} + \gamma \cdot Controls + \varepsilon_{it} \qquad (1)$$

As previously mentioned, VC investments are aggregated over the [*t-4, t*] period, whereas firm mobility is defined over the [*t+1, t+5*] window. Industry and year fixed effects are denoted by α_i and θ_t, separately, controlling for unobservable industry-specific and time-specific factors. Industry characteristics include R&D expenses, which controls for another potential channel for industry-specific technological opportunities to impact firm mobility; HHI, which measures the competitiveness of an industry; average firm size and firm size dispersion, measuring the initial dispersion of firms within an industry; industry market-to-book ratio, capturing the industry growth opportunities; industry leverage and liquidity ratios; and IPO intensity. Note that industry

R&D is measured as the logarithm of total R&D expenses of all firms in an industry during the [*t*-*4, t*] period, and IPO intensity is the total number of IPOs in [*t*-*4, t*] divided by the number of public firms in year t, to be consistent with the horizon of VC investments, while other industry characteristics take values in year *t*. Our primary interest is in β, the coefficient of VC investment.

To estimate the model, we demean all variables by industry and use year dummies as explanatory variables, and report the OLS estimation results. To secure estimates of appropriate sizes, we scale up firm mobility variables by a factor of 100. We use bootstrapped standard errors to mitigate the concern of potential heteroscedasticity and industry clustering.[8]

Table 3 reports the determinants of firm rank permutation. For each firm size measure, we report two set of estimates: estimates with only year fixed effects in column (1) and those with both industry and year fixed effects in column (2). Our focus in on (2) while using (1) for comparison. Regardless of the firm size measure and the model specification, the results consistently indicate that VC activity is associated with future creative destruction. Statistical and economic significance of the result is substantial. For example, sales-based rank permutation obtains a coefficient of 2.497 in column (2), statistically significant at the one percent level. The coefficient indicates that a 100 percent increase in VC investment leads to an increase of 0.025 in the standard deviation of sales-based rank in the subsequent five-year period, amounting to a 10 percent increase for an industry with average rank permutation (0.25). Asset-based and market capitalization-based rank permutation positive coefficients of 2.632 and 1.368, respectively, with similar statistical and economic significance (note the mean assets- and market capitalization-based rank permutations are 0.25 and 0.13, respectively).

Industry R&D receives negative coefficients in columns (1), but after controlling for fixed industry effects, its coefficients turn positive but not statistically different from zero. So incumbents' R&D investment does not influence subsequent firm mobility. This is consistent with the belief that incumbents focus on non-disruptive existing technologies (e.g., Aghion et al., 2014). It can also be interpreted as the aggregate of R&D's creative destruction effect (if any) and its entrenchment effect (Schumpeter, 1942).

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[8] Our sample has an unbalanced panel for 44 industries with a maximum of 37 years. MacKinnon and Webb (2017) show that over-rejection is a major concern even with typical clustered standard errors for this type of sample, yet two-point wild bootstrap with Rademacher weights is generally reliable.

Industry structure matters. Average firm size and industry HHI both load negatively in all three specifications, and firm size dispersion loads positively in five out of six specifications. Industries with a few large incumbents are harder to churn up, consistent with the notion that concentrated industries feature more entrenched status quo.[9] Industry market-to-book, leverage and liquidity all obtain coefficients that are positive and statistically significant in columns (1), which turn mixed after controlling for fixed industry effects, indicating the seemingly positive association is driven by certain observed industry characteristics.

[Table 3 about here]

The expected sign on IPO activity is less obvious. Following Brown and Peterson (2010) we would expect IPO activity to be positively associated with creative destruction. However, Brown and Peterson do not include venture capital investment in their estimations. After controlling for VC activity, IPO rate may instead reflect the timing decision of private investors regarding when to monetize their prior investments. The decision to change ownership by itself should not necessarily induce creative destruction. Indeed, we find that the coefficients on IPO rate in Table 3 are inconsistent in sign, with three of them positive and three of them negative.

3.3 The horizon of creative destruction

In our baseline estimates, we aggregate VC investments over rolling five-year periods and we examine firm mobility in the subsequent five-year (for sales and assets) or one-year (for market capitalization) period. The five-year horizon for the former has the effect of smoothing the VC investment measure. The five-year (one-year) horizon for the latter gives time for creative destruction to take effect. We recognize that the effect could be faster for market capitalization than for operating sizes; however, there is no theoretical guidance on the appropriate temporal lags.

[9] Rajan and Zingales (2003), Morck, Wolfenzen and Yeung (2005), and Fogel, Morck and Yeung (2008). On the other hand, one could argue that excessive concentration leads to a fragile state and encourages the entry of competition, making our prediction for this coefficient ambiguous.

In this section, we examine time horizons of different lengths for firm mobility, including 1-year, 3-year, 5-year, 7-year and 10-year horizons. We estimate model (1) with both fixed industry and year effects, record the coefficients of VC investment, and plot them in Figure 1.

[Insert Figure 1 about here]

When rank permutation is based on sales, the effects peak at the five year point and taper off after that. The coefficients of VC investment are close to each other in magnitude, and statistically significant for the one-year, three-year, and five-year horizons. A similar pattern is observed when the dependent variable is assets-based rank permutation. When considering market capitalization, the relevant coefficient is statistically and economically significant at one year (1.37), but then quickly declines thereafter. We have two observations here. First, the effect of VC investment on rank permutation is not long-lasting, and the patterns as consistent with the lifetime of VC investment. VC investment in a startup typically lasts for 4-7 years with each a profitable exit in the form of an IPO or acquisition, either of which could lead to firm rank changes, or a failure. Two, as sales and assets take time to accumulate, market capitalization as a forward-looking metric exhibits the disruptive effect in an accelerated manner as investor have anticipated part of the valuation implications of VC activity even in the first year. [10]

3.4 Alternative treatment of mergers and acquisitions

As previously discussed, there is a judgement call in how M&A activity should be treated. In this section, we treat acquiring firms different from others and acquired firms different from other delisted firms. We exclude acquiring firms whose assets exceeds 200 million dollars and grow by 50% or more for the rank permutation estimation for the five preceding years. In the case of a firm being acquired and delisted, we set its value of rank change as missing. Then we re-estimate model (1) and report the results in Table 4.

[Insert Table 4 about here]

The estimation results are very similar to those in Table 3. For all rank permutation measures, the coefficients of VC investment are all positive and statistically significant.

[10] It should be noted that this acceleration is not necessarily a mechanical implication of market efficiency. One needs to know not only that there will be winners and losers in principle, but more specifically which firms are expected winners.

Economically, an 100 percent increase in VC investment would enhance standard deviation of rank changes by an extent amounting to about 10 percent of the average standard deviation.

3.5 Subperiod Results

Venture capital rose to prominence in 1980s. In 1979, the U.S. Department of Labor issued a clarification about the Employee Retirement Income Security Act (ERISA), which freed pensions for venture capital. Venture capital activities flourished after this policy shift, so that investments in 1970s are modest compared to those in later periods. This leads to a tradeoff when selecting a date cutoff. Retaining the 1970s in our sample has the benefit of giving us greater intertemporal heterogeneity within an industry. On the other hand, the decade is quite different from the rest of our sample. To assure that our findings are not mainly attributable to the 1970s, we re-do the investigation only in post-ERISA period, i.e., 1980-2011. The results are reported in the left section of Table 5.

Note in Table 5 only estimates with fixed industry and year effects are presented. In the post-ERISA period, VC investment receives coefficients that are somewhat lower than in Table 3, 1.922. 1.824, and 1.251, for sales-, assets-, and market capitalization-based rank permutation. Yet all these coefficients remain statistically and economically significant, indicating the creative destruction effect of VC investment is pronounced in the post-ERISA period.

[Insert Table 5 about here]

Another defining regulatory event during our sample period is the National Securities Markets Improvement Act (NSMIA) in October 1996. NSMIA made it easier for private firms to sell securities to institutions and accredited investors by exempting those private sales from state regulations known as blue-sky laws. It also raised the cap on the number of investors a venture capital or private equity fund can have without registering under the Investment Company Act[11]. Ewen and Farre-Mensa (2019) show that NSMIA has facilitated the process of raising capital privately and, as a result, driven the decline of IPOs in the U.S. NSMIA increased the supply of venture capital, and had the potential to alter the VC market and its effect on firm mobility. For robustness, we divide the sample period into the Pre-NSMIA period (1975-1996) and the Post-NSMIA period (1997-2011) and re-run the estimation of model (1) in these subperiods. Pre-

[11] Such registration requires the regular disclosure of investment positions and restricts the use of leverage, among other requirements, and hence can be burdensome to fund.

NSMIA results are presented in the middle section and Post-NSMIA results in the right section of Table 5.

The coefficients of VC investment are positive and statistically significant in both the Pre- and Post-NSMIA subperiods, regardless of the firm size measure based on which rank permutation is constructed. Notable is the comparison of coefficients between the two subperiods: they are lower in magnitude in the Post-NSMIA period relative to in the pre-NSMIA period. For instance, when rank permutation is based on sales, the coefficient of VC investment is 1.795 in the Post-NSMIA period vs. 2.680 in the pre-NSMIA period, indicating weaker creative destruction effect post-NSMIA. An interpretation, which we will elaborate in a later section, is that NSMIA led to an oversupply of VC capital that became less efficient in investment. Nevertheless, even the weakened creative destruction effect in the post-NSMIA period is still economically significant. For instance, a coefficient of 1.795 indicates that doubling VC investment will give rise to an increase of 0.018 in sales-based rank permutation, equivalent to 7.2 percent of the average industry rank permutation. Such a gauge is 6.7 percent for assets-based rank permutation and 9.5 percent for market capitalization-based rank permutation.

3.6 Top 10 industries and Fama-French 12 industries

As another robustness check, we limit attention to industries in which VCs tend to be most active. Venture involvement varies substantially across industries and concentrates in a few industries. For example, the Softw (Software) industry attracted 239 billion dollars accounting for nearly 40 percent of all VC investments in our sample, whereas the Ships industry received less than one million dollars. To investigate whether our findings are driven by cross-industry variations we reexamine the results using only the top 10 industries, Softw, BusSv, Chips, Drugs, Telcm, MedEq, Hardw, Rtail, Hlth, and LabEq, which received 90 percent of total venture investments. The estimation results are qualitatively stronger than the all industry results, with VC investment's coefficients greater compared to those in the all industry regressions.

We further experiment with coarser industry definitions. Instead of Fama-French 49 industries, we create VC investment and firm mobility variables for Fama-French 12 industries and re-examine their relationship based on model (1). Excluding Money and Utilities, there are 10 industries for 1975-2011 and 370 industry-year observations. Results are reported in the right section of Table 6 and qualitatively similar.

In a summary, there exists a robust association between VC investment and the future firm mobility as measured by rank permutation in an industry.

[Insert Table 6 about here]

3.7 Industry leader turnover and firm exits

Firm rank permutation quantifies the extent to which firm rankings in an industry are churned up across the whole distribution. While all firms may be subject to the churning, more notable events may be observed at the two tails of the distribution, that is, the biggest winners may become new industry leaders, and the biggest losers may be delisted in bankruptcy or acquisition. In this section, we examine whether the creative construction effect of VC investment is strong enough to cause industry leader turnover and firm exits.

Industry leader turnover is measured as the percentage of top 10 percent firms in a Fama-French 49 industry that drop out of the top decile during the subsequent measurement period. Again, firms are ranked based on sales, assets and market capitalization, respectively, and the measurement period is five years for sales and assets and one year for market capitalization. A caveat for this measure is that very small industries could generate outlying values. In the worst case, an industry with 10 firms has one leading company per our definition, and industry leader turnover can take values of either zero or one. To avoid such integer-related artifacts, we consider only industry-years that begin with 50 or more companies at the observational year. We then use industry leader turnover as the dependent variable in model (1), and report the estimates in the left section of Table 7.

[Insert Table 7 about here]

The coefficient of VC investment is 4.196 when leader turnover is based on sales. This coefficient is statistically significant at the five percent level, and indicates that doubling VC investment will increase the five-year dropout rate of the top decile firms by 4.2 percentage points. Given the average dropout rate of 30 percent, we view this effect as economically significant. When assets-based ranking is used, the effect is even stronger with a coefficient of 4.680 that is statistically significant at the one percent level. When market capitalization-based ranking is used, VC investment obtains a coefficient of 0.807, not statistically different from zero. This seems to indicate that in the short one-year horizon, VC investment's disruptive effect is not strong enough to shake the industry leaders in terms of market capitalization.

Firm exits are measured by both the number and the rate of delisting in the subsequent five-year period. The rate is the number of delisting divided by the beginning number of public firms in a Fama-French 49 industry. In the baseline definitions, we treat all delisting as the result of creative destruction. Estimation of model (1) with exits as dependent variables is reported in the right section of Table 7. The coefficients on exits and exit rate are 24.262 and 6.929, respectively, both statistically significant at the one percent level. They indicate that holding all else constant, doubling VC investment would lead to 24, or 6.9 percent, more firms to delist on average. This effect in our view is very strong. When we exclude M&A-involved observations, the results are qualitatively unchanged.

In a summary, our findings show that VC investment is associated with subsequent churning in firm rankings within an industry, and the churning is powerful at the lower end of firm distribution and also moves the way up to affect leading companies.

3.8 Shocks to supply of VC capital

In this section, we exploit two regulatory events during our sample period that had major impacts on the supply of VC capital, in an attempt to establish the causality between VC investment and subsequent firm mobility.

The first event is the U.S. Department of Labor's clarification of the Employment Retirement Income Security Act (For parsimony, we will refer to this event as simply ERISA), which represented a major policy shift that freed pensions to invest in venture capital. Before this event, the VC industry was ignorable; after this clarification, VC investment exploded in such a way that some observers view 1980s as the meaningful beginning of the VC industry. The explosion in VC investment around 1979 indicates there was a substantial shortage of VC capital before ERISA.

Although the ERISA-caused increase of VC investment is unlikely related to the arrival of technological opportunities over all, we take a more cautious approach at the industry level to address the concern that such opportunities arrived around 1979 for some industries but no some others, which in turn led to variations in subsequent firm mobility. We average industry market-to-book ratio over the 1975-1979 period and rank industries by the average ratio, and select industries in the top quartile, and those in the bottom quartile. We view top (bottom) quartile industries as those with high (low) technological opportunities prior to ERISA. We rank industries similarly in 1984 and select the industries of high and low opportunities post ERISA. We then keep only those industries with high technological opportunities both pre- and post-ERISA, and those with low opportunities both pre- and post-ERISA. When VC capital became available, the high opportunities industries received funding while the low opportunities did not. Figure 2.1 shows the change in logged VC investment around ERISA for the high-opportunities industries and low-opportunities industries, respectively. For each group, VC investment is scaled by the level in year 1975. High opportunities industries witnessed a sharp rise in VC investment post-ERISA; in contrast, the curve for the low opportunities industries remained flat. As such the latter serves as a good control group. This allows us to conduct a difference-in-difference analysis. The literature (e.g., Kortum and Lerner, 2000) has exploited ERISA as an exogenous shock to VC investment.

[Insert Figure 2 about here]

In the sample of only high- and low-opportunities industries, we create two dummy variables: *ERISA* is set to one for year 1980 or later and zero otherwise, and *HiGrowOptions* is equal to one for high-opportunities industries and zero for low-opportunities industries. We exclude years 1980-1984 as our VC investment measures is the five-year moving average. We run the following regression:

$$Mobility_{i,[t+1,t+5]} = \alpha \cdot ERISA + \beta \cdot ERISA \times HiGrowOptions + \gamma \cdot Controls + \varepsilon_{it} \qquad (2)$$

Controls are the same as in model (1). Note that controls include industry market-to-book ratio controlling for variations in technological opportunities across industries in the sample. The coefficient of interest is β. The difference-in-difference tests are run in the full sample period (excluding 1980-1984) as well as the pre-1990 subperiod (excluding 1980-1984). The latter period meets our needs better for two reasons: one, it is not contaminated by a series of regulatory changes in 1990s[12]; two, Bertrand, Duflo and Mullainathan (2004) warns of the serial correlation bias due to longer post-treatment period.

[Insert Table 8 about here]

Estimation results are in Table 8, Panel A. The coefficient of $ERISA \times HiGrowOptions$ is statistically significant in all specifications when we use the pre-1990 period, indicating post-ERISA industries with high technological opportunities experienced significantly greater increase in firm rank permutation. For comparison, the full-period results are somewhat weaker with

[12] Notable regulatory changes in 1990s include the SEC's adoption of Rule 144A in 1990 and the several subsequent amendments to Rule 144, as well as the National Securities Markets Improvement Act (NSMIA) in 1996. They further deregulated private equity investments.

smaller coefficients on the interaction term. Also notable is that dummy variable ERISA loads positively in the full period regression but not in the pre-1990 period regression. This shows that while firm mobility increased post-ERISA overall, in the period immediately after ERISA, increased VC investment caused increased firm mobility only in high-opportunities industries.

The second regulatory event we examine is the passage of the National Securities Markets Improvement Act (NSMIA) in 1996, NSMIA exempted private sales of securities from state regulations known as blue-sky laws, and as a result, the new exemption increased significantly immediately after NSMIA (Ewens and Farre-Mensa, 2019). In addition, NISMA increased the maximum number of investors in an unregistered fund, such as a VC fund. These changes have profound implications to VC capital because they made it easier for VC funds not only to raise capital but to exit a portfolio firm.

Likewise, we select industries that are in the top market-to-book quartile in 1996 as well as in 2000 and those in the bottom quartile both pre- and post-NSMIA, and exclude years 1996-2000 from the sample. We define two dummy variables in a similar way: *NSMIA* equals one for post-NSMIA years and zero for pre-NSMIA years; *HiGrowOptions* equals one for high-opportunities industries and zero otherwise. Similarly, we consider the full sample period (excluding 1996-2000) and the 1991-2005 period (excluding 1996-2000). The estimation model is similar to (2) with *ERISA* replaced by *NSMIA*, and the interaction term being between *NSMIA* and $HiGrowOptions$.

In Panel B, Table 8, the interaction term $NSMIA \times HiGrowOptions$ does not load in any specification, and *NSMIA* also receives mixed coefficients. At the first sight, this seems inconsistent with the assumption that increased VC investment would lead to greater firm mobility. Yet Figure 2.2 shows that while VC investment increased post-NSMIA overall, it is the low-opportunities industries, not the high-opportunities industries, that experienced a much faster growth in VC investment. This tells a story of impaired investment efficiency of VC capital: as more, perhaps more than needed, supply of capital became available post-NSMIA, VC capitalists moved the money toward less promising start-ups. As a result, we fail to observe greater increase of firm mobility taking place among high-opportunities industries. From an economist's perspective, there might be an overinvestment of VC capital post-NSMIA with dwindled creative destruction effect. This is also reflected in the subperiod results in Table 5. From a methodological perspective, in the NSMIA samples, low-opportunities industries are no longer good controls and the difference-in-difference design is invalid to tell the effect of VC investment on firm mobility.

In a summary, the 1979 ERISA clarification led to an exogenous increase in VC investment in industries with high technological opportunities that had not been fully tapped, and the difference-in-difference tests verify that the efficient increase in VC investment gave rise to increased firm rank permutation. In contrast, after the 1996 NSMIA, the abundance of VC capital led to inefficient investments with lower creative destruction effects.

3.9 Spillover effect of creative destruction

In this section, we explore the extent to which VC investment in one industry is associated with creative destruction among public firm in neighboring industries. In principle, technological advances created in one industry can lead to creative destruction in other industries. For example, a positive shock to (say) oil shale technology threatens those who produce and transport coal. We may then observe destruction in the coal industry even without technological shocks to coal.

To conduct the investigation, we define a "neighbor" industry for each Fama-French 49 industry as the one that exhibits the greatest absolute correlation in annual industry stock returns during our sample period. Examples of neighbor industries include "BldMt" (Building Materials) for "Rubbr" (Rubber), "Books" for "Toys", and "BusSv" (Business Services) for "LabEq" (Lab equipment). Then we estimate model (1) using firm rank permutation in the neighbor industries and VC investment in the home industries. Control variables are for neighbor industries. We also control for fixed effects of year and the neighbor industries.

Table 9 reports the estimation results. VC investment receives positive coefficients, regardless of measures of firm mobility, which are statistically significant except in the market capitalization-based regression. This provides evidence of the existence of the spillover effect, and corroborates our earlier findings that VC investments contribute to firm mobility.

4. Conclusion

Traditional innovation research has a focus on the R&D expenses or patents, yet neither is the end result of innovative endeavors of businesses. We instead look at firm mobility, that is, the churning of firm ranking, at the industry level, as we view it as a direct measure of the creative destruction effect of innovation as well as a good gauge of the economic dynamism.

Because most radical and disruptive innovations originate from small, privately-held startups, we use the amount of VC investment as a proxy of the innovative activities in an industry. We then investigate whether and how VC investment and firm mobility among public firms are connected. We find a strong association between VC investment in an industry in a preceding five-year period and the firm rank permutation in the subsequent five- (or one-) year period. This association is robust to controlling for industry heterogeneity, different measures of firm size, different sample periods, different industry definitions as well as different treatment of M&A-involved firms. This creative destruction effect also spills over to neighboring industries.

To establish causality, we exploit the regulatory changes of the ERISA clarification in 1979 and the NSMIA in 1996. Difference-in-difference tests show that post-ERISA, industries with high technological opportunities witnessed significantly greater increase in VC investment as well as subsequent firm mobility. Post-NSMIA, in contrast, VC investment increased more in industries with low technological opportunities, leading to weaker creative destruction of VC investment overall. Our interpretation is that while VC investment leads to creative destruction, only efficient VC investment have the strong creative destruction effect.

A caveat is in order. The creative destruction effect would take shape not only among public firms but among all private and public firms. One can argue that focusing on firm mobility among public firms misses the main target, especially in an environment where financing has become never so easy for private firms and going public has lost part of its luster (e.g., Gao, Ritter and Zhu, 2013; Ewens and Mensa, 2019). Echoing this critique, the weaker results in the post-NSMIA period may be in part attributable to this type of mismeasurement of firm mobility. Yet, considering public firms are generally larger and harder to be dislodged off their positions, our measure of firm mobility likely underestimates the true strength of VC investment's creative destruction.

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Appendix A. Variable Definitions

Variable	Definition
Venture capital investment	
VC Investment	Total amount of VC deals in a Fama-French 49 industry during the past five years, measured in million U.S. dollars, adjusted by the Consumer Price Index (=100 in year 2000). In regressions, take the logarithm of one plus the amount.
Firm mobility	
Rank permutation	Standard deviation of within-industry rank change across all public firms in an industry during the subsequent period. Ranks are based on three metrics, respectively: annual sales, year-end assets and year-end market capitalization. The measurement period is 5 years for sales and assets and 1 year for market capitalization. A firms' rank is then normalized to the (0,1] range by dividing the number of public firms in the industry.
Leader turnover	Percentage of industry leaders (top decile firms) that drop out of the top decile during the subsequent period. Ranks are based on three metrics: annual sales, year-end assets, and year-end market capitalization. The measurement period is 5 years for sales and assets and 1 year for market capitalization.
Firm exits	Number and rate of firms that exit in an industry during the subsequent five-year period. Exit rate is the number of exits divided by the initial number of public firms in the industry.
Industry characteristics	
Industry R&D	Total R&D expenses in an industry in the preceding five-year period. In regressions use the logarithm of one plus R&D.
Industry market-to-book	Average market-to-book ratio across all firms in an industry-year. For a firm, market-to-book ratio is calculated as (assets - book equity + market value of equity) / assets.
Average firm size	Average firm size for an industry-year. Firm size is measured by annual sales, year-end assets, and year-end market capitalization, respectively.
Firm size dispersion	Logarithm of standard deviation in firm size for an industry-year, based on annual sales, year-end assets and year-end market capitalization, respectively.
Industry HHI	Hirfindahl-Hirschman index (HHI) of an industry, based on annual sales, year-end assets, and year-end market capitalization, respectively.
Industry leverage	Average market leverage ratio across all firms in an industry-year. For a firm, the leverage ratio is calculated as total debt / (total debt + market equity).
Industry liquidity	Average liquidity ratio across all firms in an industry-year. For a firm, the liquidity ratio is calculated as log (1 + current assets/current liabilities).
IPO intensity	Number of IPOs in the past five-year period as the ratio of the number of all public firms in an industry

Table 1. Descriptive statistics

This table presents the descriptive statistics of variables used in the paper. The sample period is 1975-2011. Variables definitions are in Appendix A. Amount of VC deals and industry R&D expenses are measured in the constant dollar of year 2000.

Variable	N	Mean	Median	Std Dev	1st percentile	99th percentile
Amount of VC deals ($ billion)	1628	1.26	0.08	5.49	0	19.97
Rank permutation: Sales	1603	0.25	0.26	0.07	0.06	0.41
Rank permutation: Assets	1603	0.25	0.26	0.07	0.06	0.40
Rank permutation: Market cap	1598	0.13	0.13	0.06	0.00	0.30
Firm exits	1423	18.9	11.0	23.9	0	112
Exit rate	1423	0.23	0.22	0.11	0	0.51
Leader turnover: Sales	805	0.30	0.26	0.21	0	1.00
Leader turnover: Assets	805	0.31	0.29	0.22	0	1.00
Leader turnover: Market cap	778	0.15	0.14	0.14	0	0.80
Industry R&D ($ billion)	1596	13.1	2.1	29.5	0	147.4
Industry market-to-book ratio	1628	1.64	1.54	0.53	0.89	3.62
Average firm size: Sales	1628	6.96	6.94	1.01	4.89	9.26
Average firm size: Assets	1628	6.98	7.00	1.08	5	9.59
Average firm size: Market cap	1628	6.80	6.87	1.25	4.06	10.12
Firm size dispersion: Sales	1628	7.64	7.59	1.15	5.23	10.32
Firm size dispersion: Assets	1628	7.72	7.75	1.20	5	10.54
Firm size dispersion: Market cap	1628	7.54	7.54	1.44	4.28	10.65
Industry HHI: Sales	1628	0.16	0.11	0.14	0.03	0.77
Industry HHI: Assets	1628	0.17	0.12	0.15	0.03	0.73
Industry HHI: Market cap.	1628	0.18	0.13	0.15	0.04	0.80
Industry leverage ratio	1607	0.27	0.27	0.11	0.06	0.51
Industry liquidity ratio	1607	1.16	1.16	0.20	0.68	1.68
IPO intensity	1628	0.28	0.21	0.26	0.00	1.20

Table 2. VC investment and subsequent firm mobility: Univariate Sorting

This table displays firm mobility following different levels of venture capital (VC) investments. VC investments are based on total dollar amount of VC deals during past five year for each of the Fama-French 49 industries. The 1,628 industry-years during 1975-2011 are classified into categories of low- (bottom quartile), intermediate (middle half), and high-VC investments (top quartile). Firm mobility is measured by rank permutation within each Fama-French 49 industry based on three different metrics: annual sales. year-end assets and market capitalization, during the subsequent five-year period (for sales and assets) or one-year period (for market capitalization). The differences in mean firm mobility between low- and high-VC investment categories and their statistical significance based on two-sample t-tests are reported. ***, **, and * mark statistical significance at the 1, 5, and 10 percent levels, respectively.

Rank permutation	VC Investment			High - Low	P-value
	Low	Intermediate	High		
Sales	0.233	0.245	0.282	0.049 ***	<0.001
Assets	0.235	0.246	0.282	0.047 ***	<0.001
Market cap.	0.119	0.133	0.151	0.032 ***	<0.001

Table 3. VC investment and firm mobility

This table presents the regressions of firm mobility on VC investment, with fixed year effects controlled for (specification (1)) or both fixed year and firm effects controlled for (specification (2)).Firm mobility is measured by firm rank permutation, the standard deviation of rank changes within a Fama-French 49 industry based on annual sales, year-end assets and market capitalization, during the subsequent five-year period (for sales and assets) or one-year period (for market capitalization), divided by the number of public firms in the industry, and then scaled up by a factor of 100. VC investment is measured by the logarithm of (1 + total dollar amount of VC deals), in a Fama-French 49 industry during the past five-year period. Control variables include industry characteristics as defined in Appendix A. Bootstrapped standard errors are reported in the parentheses. ***, **, and * mark statistical significance at the 1, 5, and 10 percent levels, respectively.

	Sales		Assets		Market Cap.	
	(1)	(2)	(1)	(2)	(1)	(2)
VC investment	2.156 ***	2.497 ***	2.225 ***	2.632 ***	1.215 ***	1.368 ***
	(0.464)	(0.465)	(0.447)	(0.501)	(0.379)	(0.431)
Industry R&D	-0.459 ***	0.176	-0.510 ***	0.132	-0.116	0.190
	(0.125)	(0.223)	(0.126)	(0.230)	(0.080)	(0.194)
Average firm size	-4.876 ***	-2.607 **	-4.833 ***	-4.805 ***	-2.326 ***	-0.316 ***
	(1.102)	(1.033)	(0.932)	(0.888)	(0.620)	(0.121)
Firm size dispersion	4.329 ***	2.478 ***	4.601 ***	3.898 ***	1.477 ***	-0.191
	(0.753)	(0.843)	(0.602)	(0.701)	(0.461)	(0.303)
Industry HHI	-9.625 ***	-3.790 ***	-8.801 ***	-3.905 ***	-2.047 *	-0.507
	(1.723)	(1.163)	(1.714)	(1.236)	(1.195)	(1.089)
Industry market-to-book	3.084 ***	-1.296 **	3.008 ***	-0.771	2.081 ***	1.128 **
	(0.940)	(0.627)	(1.057)	(0.636)	(0.790)	(0.544)
Industry leverage	29.098 ***	1.637	26.961 ***	2.269	17.569 ***	9.978 ***
	(8.485)	(3.386)	(8.470)	(3.527)	(4.914)	(1.964)
Industry liquidity	7.151 ***	-0.485	6.869 ***	-4.231 **	3.908 ***	0.992
	(0.957)	(2.265)	(0.964)	(2.005)	(0.708)	(1.767)
IPO intensity	0.324	-4.426 ***	0.203	-4.196 ***	1.011	-0.847
	(1.404)	(0.910)	(1.343)	(0.988)	(1.001)	(0.927)
Constant	34.610 ***		33.998 ***		15.383 ***	
	(6.132)		(6.095)		(3.233)	
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	No	No	No	Yes	No	Yes
N	1,580	1,580	1,580	1,580	1,576	1,576
R^2	0.307	0.197	0.299	0.191	0.240	0.187

Table 4. VC Investment and firm mobility: Treating M&As

This table presents the regressions of firm mobility on VC investment in the sample where M&A-involved firm-year observations are excluded for computing firm mobility measure. Firm mobility is measured by firm rank permutation, the standard deviation of rank changes within a Fama-French 49 industry based on annual sales, year-end assets and market capitalization, during the subsequent five-year period (for sales and assets) or one-year period (for market capitalization), divided by the number of public firms in the industry, and then scaled up by a factor of 100. VC investment is measured by the logarithm of (1 + total dollar amount of VC deals), in a Fama-French 49 industry during the past five-year period. Control variables include industry characteristics as defined in Appendix A. Bootstrapped standard errors are reported in the parentheses. ***, **, and * mark statistical significance at the 1, 5, and 10 percent levels, respectively.

	Sales		Assets		Market Cap.	
	(1)	(2)	(1)	(2)	(1)	(2)
VC investment	2.270 ***	2.683 ***	2.221 ***	2.554 ***	1.284 ***	1.008 ***
	(0.431)	(0.436)	(0.425)	(0.445)	(0.368)	(0.382)
Industry R&D	-0.410 ***	-0.474 **	-0.396 ***	-0.699 ***	-0.054	0.127
	(0.112)	(0.223)	(0.113)	(0.225)	(0.078)	(0.183)
Average firm size	-4.226 ***	-0.941 *	-4.208 ***	-1.465 ***	-1.851 ***	-0.766 *
	(0.841)	(0.508)	(0.797)	(0.461)	(0.558)	(0.393)
Firm size dispersion	3.420 ***	0.608	3.434 ***	1.025 ***	0.902 *	0.478
	(0.629)	(0.427)	(0.597)	(0.397)	(0.459)	(0.328)
Industry HHI	-3.224 *	0.443	-3.037 *	0.660	2.892 **	1.845 *
	(1.699)	(1.249)	(1.696)	(1.144)	(1.283)	(0.951)
Industry market-to-book	2.814 ***	-1.490 ***	3.135 ***	-0.445	3.412 ***	1.983 ***
	(0.730)	(0.563)	(0.821)	(0.568)	(0.700)	(0.473)
Industry leverage	25.227 ***	4.620 ***	25.363 ***	7.005 ***	17.201 ***	3.054 ***
	(6.007)	(1.462)	(6.029)	(1.380)	(4.211)	(1.163)
Industry liquidity	7.506 ***	0.893	7.174 ***	0.873	2.533 ***	0.222
	(0.884)	(0.679)	(0.932)	(0.617)	(0.688)	(0.538)
IPO intensity	-0.186	-4.240 ***	0.123	-3.065 ***	1.248	-0.383
	(1.209)	(1.025)	(1.213)	(0.965)	(0.928)	(0.846)
Constant	29.510 ***		29.595 ***		15.996 ***	
	(2.707)		(2.763)		(2.709)	
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	No	Yes	No	Yes	No	Yes
N	1,576	1,576	1,576	1,576	1,573	1,573
R^2	0.338	0.263	0.334	0.247	0.195	0.126

Table 5. Subperiod results

This table presents the regressions of firm mobility on VC investment in the Post-ERISA period (1981-2011), pre-NSMIA period (1975-1996) and post-NSMIA period (1997-2011), respectively. Firm mobility is measured by rank permutation based on sales, assets, and market capitalization. Rank permutation is the standard deviation of rank changes within a Fama-French 49 industry during the subsequent five-year period (for sales and assets) or one-year period (for market capitalization), divided by the number of public firms in the industry, and then scaled up by a factor of 100. VC investment is measured by the logarithm of (1 + total dollar amount of VC deals), in a Fama-French 49 industry during the past five-year period. Control variables include industry characteristics as defined in Appendix A. Bootstrapped standard errors are reported in the parentheses. ***, **, and * mark statistical significance at the 1, 5, and 10 percent levels, respectively.

	Post-ERISA			Pre-NSMIA			Post-NSMIA		
	Sales	Assets	Market cap	Sales	Assets	Market cap	Sales	Assets	Market cap
VC investment	1.922 ***	1.824 ***	1.251 **	2.680 ***	2.912 ***	1.309 **	1.795 ***	1.676 **	1.234 **
	(0.597)	(0.588)	(0.515)	(0.735)	(0.722)	(0.609)	(0.647)	(0.713)	(0.596)
Industry R&D	-0.255	-0.121	0.334	0.687 **	0.442	0.148	-0.541 *	-0.299	0.252
	(0.265)	(0.275)	(0.235)	(0.316)	(0.299)	(0.266)	(0.323)	(0.343)	(0.320)
Average firm size	-1.373	-4.125 ***	0.125	-2.194 *	-4.317 ***	-0.317 **	-4.962 ***	-7.296 ***	0.050
	(1.354)	(1.195)	(0.201)	(1.333)	(1.166)	(0.167)	(1.691)	(1.556)	(0.309)
Firm size dispersion	1.845 *	3.319 ***	-0.777 *	2.288 **	4.002 ***	0.142	4.164 ***	5.267 ***	-1.015 *
	(1.115)	(0.914)	(0.399)	(1.153)	(0.930)	(0.391)	(1.294)	(1.252)	(0.543)
Industry HHI	-3.131 **	-4.380 ***	0.572	-2.886 **	-2.099	-1.469	-9.277 ***	-11.235 ***	-0.187
	(1.472)	(1.447)	(1.389)	(1.628)	(1.508)	(1.543)	(1.930)	(1.959)	(1.702)
Industry market-to-book	-0.463	-0.029	0.800	-2.481 ***	-1.861 **	0.589	0.096	0.409	1.196
	(0.715)	(0.742)	(0.613)	(0.856)	(0.886)	(0.732)	(0.894)	(0.942)	(0.829)
Industry leverage	3.998	5.395	11.540 ***	-3.058	-0.858	6.908 ***	8.371 *	7.556	13.566 ***
	(3.380)	(3.794)	(2.339)	(4.737)	(4.798)	(2.620)	(4.884)	(5.162)	(3.068)
Industry liquidity	-2.455	-6.090 **	1.673	4.735	2.005	2.994	-10.370 ***	-15.645 ***	0.128
	(2.700)	(2.354)	(2.122)	(2.965)	(2.860)	(2.162)	(3.161)	(2.852)	(2.766)
IPO intensity	-1.933	-1.654	1.635	-6.560 ***	-6.206 ***	-2.846 ***	1.158	1.566	3.321 **
	(1.294)	(1.253)	(1.129)	(1.183)	(1.101)	(1.101)	(1.864)	(1.914)	(1.816)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,149	1,149	1,145	930	930	928	650	650	648
R^2	0.171	0.180	0.213	0.236	0.212	0.142	0.207	0.234	0.270

Table 6. VC Investment and firm mobility: Top 10 industries and FF-12 industries

This table presents the regressions of firm rank permutation on VC investment in the sample consisting of the top 10 Fama-French 49 industries with the largest amounts of VC investment (Left) and in Fama-French 12 industries (Right). Firm rank permutation, based on annual sales, year-end assets and market capitalization, is measured as the standard deviation of rank changes within an industry during the subsequent five-year (for sales and assets) or one-year (for market capitalization) period, divided by the number of firms in the industry, and then scaled up by a factor of 100. VC investment is measured by the logarithm of (1 + total dollar amount of VC deals), in an industry during the past five-year period. Control variables include industry characteristics as defined in Appendix A. Bootstrapped standard errors are reported in the parentheses. ***, **, and * mark statistical significance at the 1, 5, and 10 percent levels, respectively.

	Top 10 FF-49 industries			FF-12 industries		
	Sales	Assets	Market cap	Sales	Assets	Market cap
VC investment	2.705 ***	2.883 ***	1.729 **	1.789 ***	1.633 ***	0.844 *
	(0.772)	(0.756)	(0.709)	(0.508)	(0.509)	(0.476)
Industry R&D	0.343	0.351	-0.068	-0.281	-0.317	-0.727
	(0.455)	(0.453)	(0.370)	(0.506)	(0.456)	(0.485)
Average firm size	-3.584 **	-3.490 **	-0.222	-0.956	-0.667	-1.787 **
	(1.658)	(1.519)	(0.243)	(0.884)	(0.618)	(0.802)
Firm size dispersion	1.593	1.630	0.395	0.419	0.062	2.524 ***
	(1.377)	(1.219)	(0.617)	(0.792)	(0.659)	(0.756)
Industry HHI	-3.498	-3.994	-2.042	-9.536 **	-7.979 **	-13.114 ***
	(2.907)	(2.778)	(2.559)	(3.919)	(3.685)	(3.828)
Industry market-to-book	1.442	1.216	0.692	1.457	1.650	1.354
	(1.210)	(1.267)	(1.036)	(1.181)	(1.078)	(1.127)
Industry leverage	8.457	8.308	6.318	5.395	6.689	4.974
	(5.957)	(5.945)	(5.053)	(4.445)	(4.233)	(3.644)
Industry liquidity	10.986 ***	10.814 ***	3.077	-0.221	-0.088	2.936 **
	(3.783)	(3.994)	(3.832)	(1.150)	(1.035)	(1.260)
IPO intensity	-3.026 *	-3.050	0.878	-1.378	-1.285	-0.239
	(1.784)	(1.889)	(1.781)	(2.073)	(1.783)	(1.913)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	370	370	370	370	370	370
R^2	0.524	0.536	0.513	0.488	0.511	0.967

Table 7. VC investment and firm mobility at tails of distribution

This table presents the regressions of leader turnover and firm exits on VC investment. Leader turnover is the percentage of top decile firms in an Fama-French 49 industry that drop out of the top decile in the subsequent 5-year period. Only industries with at least 50 public firms at the observational year are considered. Ranks are based on annual sales, year-end assets and market capitalization, respectively. Exits are measured by the number of firms in an Fama-French 49 industry that exit the public stock market in the subsequent five-year period, and the rate, i.e., the number of exits divided by the number of public firms in year 0. VC investment is measured by the logarithm of (1 + total dollar amount of VC deals), in a Fama-French 49 industry during the past five-year period. Control variables include industry characteristics as defined in Appendix A. Bootstrapped standard errors are reported in the parentheses. ***, **, and * mark statistical significance at the 1, 5, and 10 percent levels, respectively.

	Leader turnover			Firm exits	
	Sales	Assets	Market cap.	Exits	Exit rate
VC investment	4.196 **	4.680 ***	0.807	24.262 ***	6.929 ***
	(1.917)	(1.817)	(1.528)	(1.430)	(0.873)
Industry R&D	2.147 *	0.832	0.127	1.106	0.145
	(1.165)	(1.098)	(0.922)	(0.734)	(0.414)
Average firm size	3.531	-0.358	0.104	0.123	-0.293
	(3.866)	(3.948)	(0.417)	(0.411)	(0.228)
Firm size dispersion	-6.741 **	-0.082	-2.161 **	-2.465 **	1.225 **
	(3.253)	(3.285)	(1.002)	(0.966)	(0.547)
Industry HHI	-10.919 **	-2.441	-0.432	-14.370 ***	-6.984 ***
	(4.705)	(5.038)	(3.797)	(3.585)	(1.870)
Industry market-to-book	9.169 ***	9.822 ***	1.608	7.986 ***	-1.720
	(2.236)	(2.240)	(1.896)	(1.762)	(1.050)
Industry leverage	39.488 ***	33.835 ***	-16.496 **	15.718 **	-1.269
	(10.399)	(11.068)	(7.165)	(6.870)	(6.342)
Industry liquidity	-37.931 ***	-49.096 ***	-10.657 *	6.714	2.880
	(8.336)	(7.205)	(5.857)	(5.588)	(3.317)
IPO intensity	3.925	1.212	2.452	-7.332 **	-7.023 ***
	(4.103)	(4.299)	(3.953)	(3.082)	(1.604)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
N	802	802	775	1,408	1,408
Within R^2	0.198	0.231	0.112	0.586	0.501

Table 8. Difference-in-difference tests

This table presents the difference-in-difference test of firm rank permutation on VC investment around two regulatory events: the 1979 clarification about ERISA (Panel A), and the passage of NSMIA in 1996 (Panel B). For either event, the full sample period as well as a 15-year symmetric window are used for the analyses, with a five-year event window (1980-1984 for ERISA and 1996-2000 for NSMIA) period is excluded from either period. Firm rank permutation, based on sales, assets, and market capitalization, respectively, is the standard deviation of rank changes within a Fama-French 49 industry during the subsequent five-year (for sales and assets) or one-year period (for market capitalization), divided by the number of public firms in the industry, and then scaled up by a factor of 100. VC investment is measured by the logarithm of (1 + total dollar amount of VC deals), in a Fama-French 49 industry during the past five-year period. *ERISA (NSMIA)* is a dummy variable that is set to one for post-1979 (post-1996) observations and zero otherwise. *HiGrowOptions* is a dummy variable equal to one for industries with top quartile market-to-book ratios in both pre- and post-event windows and zero for industries with bottom quartile market-to-book ratios in both pre- and post-event windows. Other industries are excluded. Control variables include industry characteristics as defined in Appendix A. OLS estimation is employed with standard errors reported in the parentheses. ***, **, and * mark statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A. Around ERISA

	Sales		Assets		Market Cap.	
	Full period	Pre-1990	Full period	Pre-1990	Full period	Pre-1990
ERISA	3.244 **	2.363	3.137 **	2.609	3.184 ***	0.882
	(1.319)	(1.816)	(1.284)	(1.900)	(1.206)	(1.756)
ERISA×HiGrowOptions	3.679 ***	10.238 ***	3.839 ***	10.872 ***	1.610	4.249 *
	(1.185)	(2.891)	(1.180)	(2.890)	(1.116)	(2.421)
Industry market-to-book	-1.590	-5.738 **	-1.769	-4.833 *	0.801	-1.253
	(1.147)	(2.268)	(1.172)	(2.465)	(1.162)	(2.473)
Industry R&D	-0.127	0.151	-0.223	0.298	-0.499 ***	-0.308
	(0.201)	(0.347)	(0.178)	(0.314)	(0.154)	(0.311)
Average firm size	-8.909 ***	1.918	-10.154 ***	-1.403	-8.386 ***	-6.095 ***
	(1.306)	(2.694)	(1.341)	(2.775)	(1.197)	(2.261)
Firm size dispersion	6.221 ***	-2.283	7.308 ***	-0.526	7.008 ***	5.009 ***
	(1.152)	(2.283)	(1.166)	(2.298)	(0.978)	(1.832)
Industry HHI	-14.454 ***	4.125	-18.746 ***	2.466	-8.368 ***	-5.738
	(3.493)	(5.423)	(3.107)	(5.579)	(2.354)	(4.506)
Industry leverage	-2.251	-8.000	-6.832	1.409 ***	-1.876	-1.125
	(5.190)	(9.998)	(5.256)	(10.200)	(0.465)	(9.050)
Industry liquidity	-2.622	-7.568 **	-4.472 *	-10.539 ***	-0.185	-6.223
	(2.380)	(3.760)	(2.424)	(3.971)	(2.163)	(3.928)
IPO intensity	1.711	1.076	0.972	-0.531	1.069	3.311
	(1.766)	(2.934)	(1.864)	(3.176)	(1.743)	(2.041)
Constant	44.945 ***	43.030 ***	50.750 ***	50.854 ***	31.430 ***	38.646 ***
	(4.842)	(7.640)	(4.902)	(8.253)	(4.736)	(8.123)
N	323	120	323	120	323	120
R^2	0.407	0.321	0.425	0.342	0.341	0.331

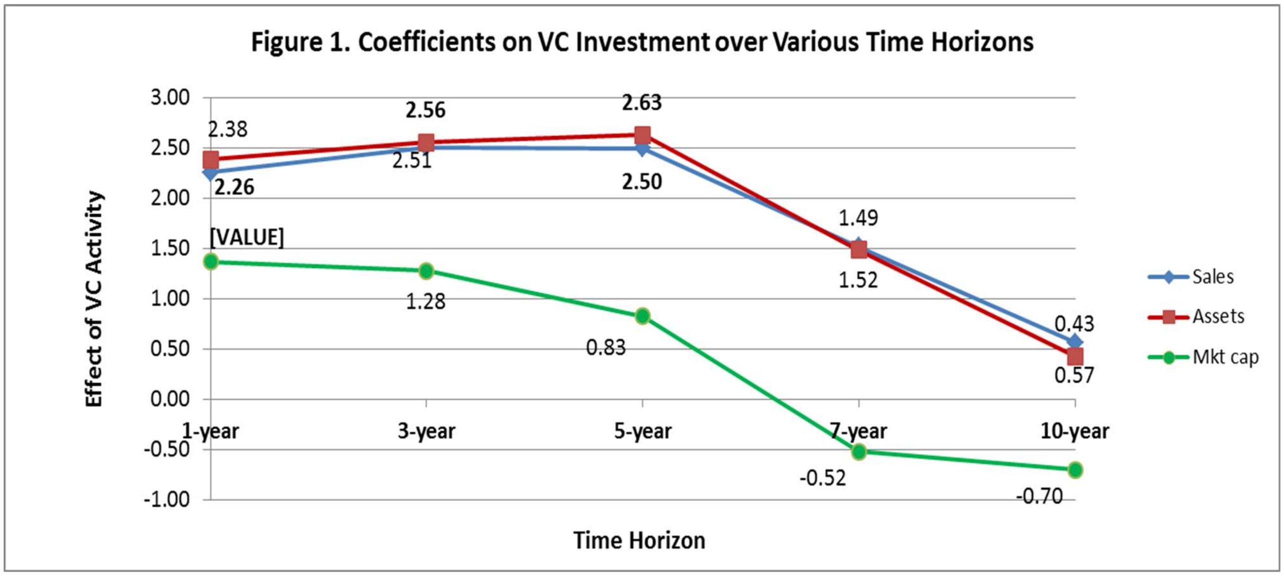
Panel B. Around NSMIA

	Sales		Assets		Market Cap.	
	Full period	1991-2005	Full period	1991-2005	Full period	1991-2005
NSMIA	-2.431 ***	-1.361	-2.989 ***	-2.157 *	2.157 ***	2.598 **
	(0.947)	(1.252)	(0.944)	(1.203)	(0.727)	(1.145)
NSMIA×HiGrowOptions	-0.323	-2.565	1.276	0.257	-0.458	-1.099
	(1.377)	(1.571)	(1.330)	(1.509)	(1.050)	(1.480)
Industry market-to-book	-1.048	-0.846	-0.603	-1.516	1.103	2.056 *
	(0.936)	(1.279)	(0.924)	(1.289)	(0.748)	(1.206)
Industry R&D	-0.355 **	-1.011 ***	-0.317 **	-1.037 ***	-0.202 *	-0.300
	(0.166)	(0.257)	(0.147)	(0.233)	(0.111)	(0.190)
Average firm size	-6.772 ***	-14.844 ***	-7.132 ***	-14.019 ***	-4.463 ***	-4.764 ***
	(0.939)	(1.282)	(0.918)	(1.280)	(0.719)	(1.208)
Firm size dispersion	6.104 ***	13.302 ***	6.222 ***	12.066 ***	3.021 ***	2.973 ***
	(0.940)	(1.333)	(0.897)	(1.274)	(0.672)	(1.121)
Industry HHI	-15.457 ***	-10.302 ***	-13.813 ***	-6.959 **	-4.984 ***	-2.358
	(2.600)	(3.321)	(2.417)	(3.208)	(1.741)	(3.257)
Industry leverage	-16.256 ***	6.762	-14.428 ***	6.205	-4.866	0.327
	(4.380)	(5.890)	(4.263)	(5.762)	(3.274)	(5.334)
Industry liquidity	-1.035	13.792 **	-2.142	14.567 ***	-1.052	1.698
	(2.334)	(3.736)	(2.258)	(3.743)	(1.714)	(2.988)
IPO intensity	1.129	-6.848 **	1.135	-4.089	2.026 *	3.324
	(1.564)	(2.651)	(1.529)	(2.647)	(1.216)	(2.703)
Constant	39.149 ***	22.825 ***	40.151 ***	25.864 ***	22.660 ***	19.008 ***
	(4.709)	(6.699)	(4.555)	(6.614)	(3.355)	(5.383)
N	523	181	523	181	522	179
R^2	0.279	0.649	0.295	0.641	0.189	0.285

Table 9. VC Investment and firm mobility in neighbor industries

This table presents the regressions of firm rank permutation on VC investment in the neighboring industry. For each Fama-French 49 industry, a neighbor industry is identified as the industry that exhibits the highest absolute correlation of annual stock returns with the home industry. Firm rank permutation, based on annual sales, year-end assets and market capitalization, respectively, is measured as the standard deviation of rank changes within a Fama-French 49 industry during the subsequent five-year (for sales and assets) or one-year (for market capitalization) period. VC investment is measured by the logarithm of (1 + total dollar amount of VC deals), in a Fama-French 49 industry during the past five-year period. Control variables include industry characteristics as defined in Appendix A. Bootstrapped standard errors are reported in the parentheses. ***, **, and * mark statistical significance at the 1, 5, and 10 percent levels, respectively.

Firm rank permutation based on:	Sales		Assets		Market cap	
VC investment	0.317	**	0.547	***	0.262	
	(0.142)		(0.146)		(0.192)	
Industry R&D	-0.100	*	-0.118	**	0.010	
	(0.054)		(0.056)		(0.075)	
Average firm size	-0.622	***	-0.407	***	-0.240	**
	(0.076)		(0.078)		(0.099)	
Firm size dispersion	-0.395		-0.424	*	-0.887	***
	(0.265)		(0.239)		(0.299)	
Industry HHI	2.412		9.856	***	5.528	***
	(2.338)		(1.338)		(1.347)	
Industry market-to-book	1.609	***	1.465	***	2.249	***
	(0.310)		(0.348)		(0.523)	
Industry leverage	6.339	***	3.682	***	-1.493	
	(0.864)		(0.928)		(1.180)	
Industry liquidity	0.470		-0.189		-1.251	***
	(0.299)		(0.298)		(0.427)	
IPO intensity	1.569	***	2.044	***	1.534	**
	(0.595)		(0.604)		(0.767)	
Year fixed effects	Yes		Yes		Yes	
Industry fixed effects	Yes		Yes		Yes	
N	1,559		1,559		1,559	
R^2	0.197		0.245		0.312	



Note: This figure shows the coefficients on VC investments when firm rank permutation is measured over different post-investment time horizons. Rank permutation is based on annual sales, year-end assets and market capitalizations, respectively. The standard deviations of rank change over 1-year, 3-year, 5-year, 7-year and 10-year periods are examined. Coefficients in bold have statistical significance at the 10 percent or lower level.

Figure 2.1 VC Investments Around ERISA

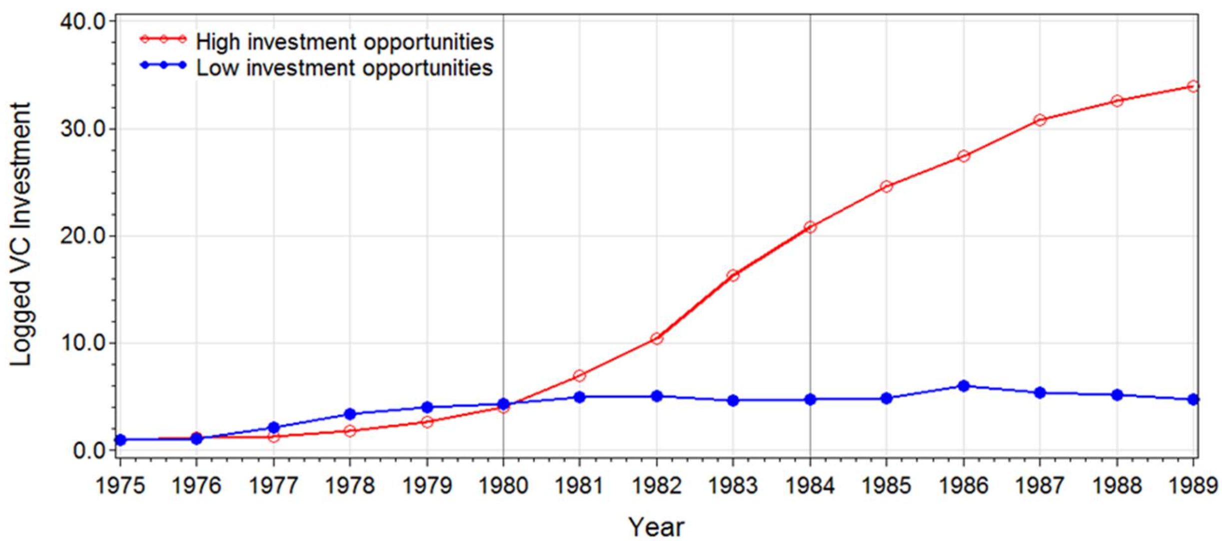
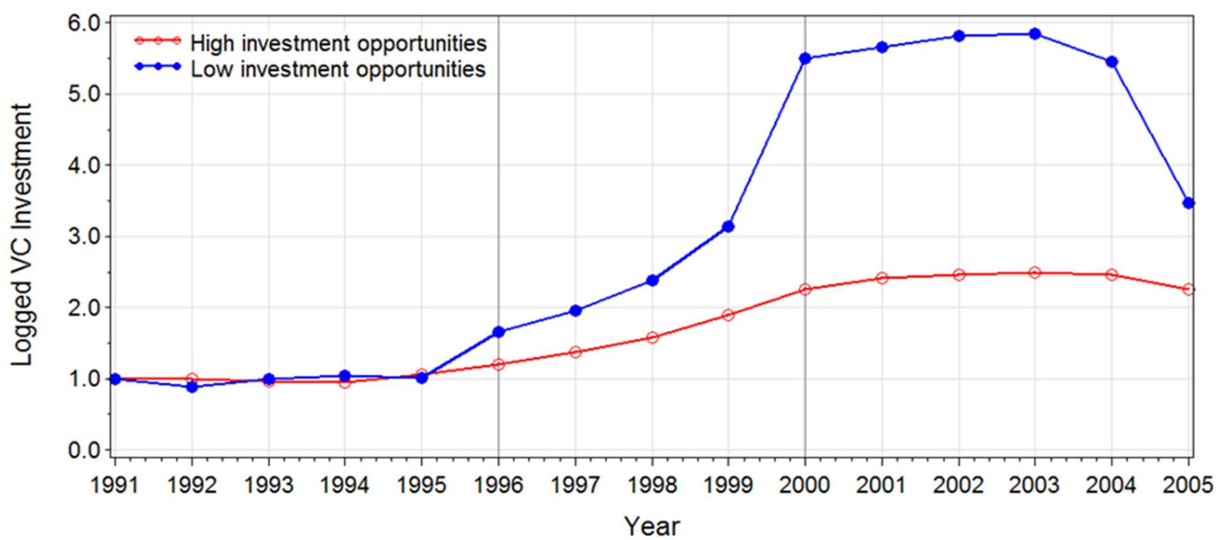


Figure 2.2 VC Investments Around NSMIA



Note: These figures exhibit the changes of VC investment in industries with high investment opportunities vs those with low investment opportunities around ERISA (Figure 2.1) and NSMIA (Figure 2.2), respectively. An industry with top (bottom) quartile market-to-book ratios both pre- and post-event are classified as one with stable high (low) investment opportunities. On the vertical axis, logged five-year VC investment is scaled by the starting level in 1975 and 1991, respectively.