

Investment Cycles and Startup Innovation*

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Abstract

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JEL Classification: G24, G32, O31

Key Words: Venture Capital, Innovation, Market Cycles, Financing Risk

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Abstract

We find that VC-backed firms receiving their initial investment in hot markets are less likely to IPO, but conditional on going public are valued higher on the day of their IPO, have more patents and have more citations to their patents. Our results suggest that VCs invest in riskier and more innovative startups in hot markets (rather than just worse firms). This is true even for the most experienced VCs. Furthermore, our results suggest that the flood of capital in hot markets also plays a *causal* role in shifting investments to more novel startups - by lowering the cost of experimentation for early stage investors and allowing them to make riskier, more novel, investments.

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“Our willingness to fail gives us the ability and opportunity to succeed where others may fear to tread.” - Vinod Khosla on his venture firms innovative success.

I. Introduction

It is well known that the financing available for startups that commercialize new technologies is extremely volatile. These “investment cycles” have been extensively studied in the literature on venture capital (Gompers and Lerner (2004), Kaplan and Schoar (2005), Gompers et al. (2008)), but have also been documented in historical work linking financial market activity to radical innovations in manufacturing, communications and transportation going back to the mid 1700s (Kindleberger (1978); Perez (2002)). Conventional wisdom and much of the popular literature tends to associate these cycles with negative attributes. Herding among investors is believed to lead to an excess supply of capital in the market (Scharfstein and Stein (1990)), lowering the discipline of external finance and leading to more “junk” and “me-too” ventures getting financed in hot markets (Gupta (2000)).

However, an alternative view suggests that periods of heated activity in the financing of startups may also be associated with better investment opportunities (Gompers et al. (2008), Pastor and Veronesi (2005)). In addition, Nanda and Rhodes-Kropf (2011) argue that the abundance of capital in such times may also allow investors to experiment more effectively, thereby shifting the type of startups that investors finance towards those that are neither better nor worse but more risky and innovative.

According to this latter view, the abundance of capital associated with investment cycles may not just be a response to the arrival of new technologies, but may in fact play a critical role in driving the commercialization and diffusion of new technologies. It also suggests that looking only at the failure rates for firms funded in hot markets is not sufficient to infer that more

“junk” is funded in such times. Greater failures can also result from more experimentation, so that simultaneously examining the degree of success for the firms that did not fail may be key to distinguishing between a purely negative view of investment cycles and one that suggests it also facilitates experimentation.

We study the ultimate outcome for venture capital-backed startups that were first funded between 1980 and 2004. We find that startups receiving their initial funding in quarters when many other startups were also funded were less likely to IPO (and more likely to go bankrupt) than those founded in quarters when fewer firms were funded. Conditional on being successful enough to go public, however, startups funded in more active periods were valued higher on the day of their IPO, had a higher number of patents and received more citations to their patents. Our results suggest that more novel, rather than *just* “worse” firms, seem to be funded in boom times.¹

We further examine whether more novel firms being funded in boom times is being driven by the entry of different investors during these periods, or whether the same investors seem to change their investments across the cycle. When we include investor fixed effects our estimations suggest that the results are not being driven by uninformed investors entering during hot times, but rather by the current investors changing their investments. Furthermore, when we reduce the sample to those investors with greater than 25 investments from 1980-2004 (the most active 7%), we find that even the most experienced investors back riskier, more innovative startups in boom times.

An obvious question about the observed correlation between hot markets and the funding of more novel startups is whether the hot markets are purely a response to different investment opportunities where the type of startup is more novel, or whether the abundance of capital also *changes* the type of firm that investors are willing to finance in such times (independent

¹The idea that worse projects are funded during hot times is likely true - we are suggesting that simultaneously riskier, more innovative projects are funded.

of the investment opportunities at different points in the cycle).

In order to shed light on this question, we exploit the fact that the supply of capital into the VC industry is greatly influenced by the asset allocation of limited partners putting money into ‘private equity’ more broadly. We therefore use an instrumental variables estimation strategy, where the number of startup firms financed in a given quarter is instrumented with a variable that measures the number of *leveraged buyout funds* that were raised in the 5-8 quarters before the firm was funded. The assumption is that the limited partners decisions to invest in buyout funds are uncorrelated with the opportunity set in early stage venture capital, since buyout funds focus on turnarounds of existing companies while early stage investors focus on new technologies and opportunities. However, the fact that limited partners allocate capital to the ‘private equity’ asset class as a whole leads fundraising by venture and buyout funds to be associated. Our instrumental variables approach should capture that part of the VC investments that are due to increases in capital unrelated to the investment opportunities available at the time for venture capital funds. Lagged buyout fundraising is used as an instrument to account for the fact that venture funds take 1-3 years to fully invest the capital in their funds and has the added advantage of further distancing the instrument from current VC opportunities. Our results are robust to this IV strategy, suggesting that after accounting for the level of investment due to differential opportunities in the cycle, increased capital in the industry seems to *change* the type of startup that VCs fund, towards firms that are more novel. This finding also holds when we include investor fixed effects, including for the most experienced investors. Thus, increased capital in the venture industry seems to alter how even the more experienced venture capitalists invest. These findings are consistent with a view that an abundance of capital causes investors to increase experimentation, making them more willing to fund risky and innovative startups in boom times (Nanda and Rhodes-Kropf (2011)).

Thus, our work is related to a growing body of work that considers the role of financial

intermediaries on innovation and new venture formation (see Kortum and Lerner (2000), Hellmann (2002), Lerner et al. (2011), Sorensen (2007), Tian and Wang (2011), Hochberg et al. (2007), Hellmann and Puri (2002), Mollica and Zingales (2007), Samila and Sorenson (2011), Bengtsson and Sensoy (2011)). Our results suggest that rather than just reducing frictions in the availability of capital for new ventures, investment cycles may play a much more central role in the diffusion and commercialization of technologies in the economy. Financial market investment cycles may create innovation cycles.

Our findings are also complementary to recent work examining how R&D by publicly traded firms responds to relaxed financing constraints (Brown et al. (2009), Li (2012)). While this work is focused on the intensive margin of R&D, our work examines how shifts in the supply of capital impacts the choice of firms that investors might choose to fund, thereby having a bearing on the extensive margin of innovation by young firms in the economy.

Our results are also related to a growing body of work examining the relationship between the financing environment for firms and startup outcomes. Recent work has cited the fact that many Fortune 500 firms were founded in recessions as a means of showing how cold markets lead to the funding of great companies (Stangler (2009)). We note that our results are consistent with this finding. In fact, we document that firms founded in cold markets are significantly more likely to go public. However, we propose that hot markets may not only lead to lower discipline among investors, but also seem to facilitate the experimentation that is needed for the commercialization and diffusion of radical new technologies. Hot markets allow investors to take on more risky investments, and may therefore be a critical aspect of the process through which new technologies are commercialized. Our results are therefore also relevant for policy makers who may be concerned about regulating the flood of capital during such investment cycles.

The rest of the paper is structured as follows. In Section 2, we develop our hypothesis

around the relationship between financing environment and startup outcomes. In Section 3, we provide an overview of the Data that we use to test the hypothesis. We outline our empirical strategy and discuss our main results in Section 4. Section 5 concludes.

II. Financing Environment and Startup Outcomes

Popular accounts of investment cycles have highlighted the large number of failures that stem from investments made in good times and noted that many successful firms are founded in recessions. A natural inference is that boom times lower the discipline of external finance and lead investors to make worse investments when money is chasing deals. The underlying assumption behind this inference is that as the threshold for new firms to be founded changes in boom times, so that the marginal firm that gets funded is weaker. Looking at the average pool of entrants is therefore sufficient to understand how the change in the financing environment for new firms is associated with the type of firm that is funded.

However, understanding the extent to which a firm is weaker *ex ante* is often very difficult for venture capital investors, who may be investing in new technologies, as-yet-non-existent markets and unproven teams. In fact, much of venture capitalist’s successes seem to stem from taking informed bets with startups and effectively terminating investments when negative information is revealed about these firms (Metrick and Yasuda (2010)). For example, Sahlman (2010) notes that as many as 60% of venture-capitalist’s investments return less than their cost to the VC (either through bankruptcy or forced sales) and that about 10% of the investments – typically the IPOs – effectively make all the returns for the funds. Sahlman points to the example of Sequoia Capital, that in early 1999 “placed a bet on an early stage startup called Google, that purported to have a better search algorithm” (page 2). Sequoia’s \$12.5 million investment was worth \$4 billion when they sold their stake in the firm in 2005, returning 320

times their initial cost.

Google was by no means a sure-shot investment for Sequoia Capital in 1999. The search algorithm space was already dominated by other players such as Yahoo! and Altavista, and Google may just have turned out to be a “me too” investment. In fact, Bessemer Ventures, another renowned venture capital firm had the opportunity to invest in Google because a friend of partner David Cowan had rented her garage to Google’s founders, Larry Page and Sergey Brin. On being asked to meet with the two founders, Cowan is said to have quipped, “Students? A new search engine? ... How can I get out of this house without going anywhere near your garage?” (<http://www.bvp.com/portfolio/antiportfolio.aspx>) In fact, Bessemer ventures had the opportunity to, but chose not to invest in several other such incredible successes, including Intel, Apple, Fedex, Ebay and Paypal.

The examples above point to the fact that while VCs may not be able to easily distinguish good and bad investment opportunities *ex ante*, they may have a better sense of how risky a potential investment might be. An investment that is more risky *ex ante* will be more likely to fail. In this sense, an *ex post* distribution of risky investments can look a lot like an *ex post* distribution of worse investments. However, on average the successes in risky investments will be bigger than less risky ones, while worse investments will do badly regardless. Figure 1 highlights how the *ex post* distribution of risky investments differs from the *ex post* distribution of worse investments. That is, rather than a shift in the distribution of outcomes to the left (or the right if investments are consistently better), riskier investments lead to a twist in the distribution of outcomes, with greater failures, but a few, bigger successes. Nanda and Rhodes-Kropf (2011) propose that investors may fund riskier investments in hot markets as these times allow investors to experiment more effectively. If this is the case, then we should expect to see fewer successes and more failures for firms funded in hot markets. However, conditional on a successful outcome such as an IPO, we would expect firms funded in hot markets to do

even better.

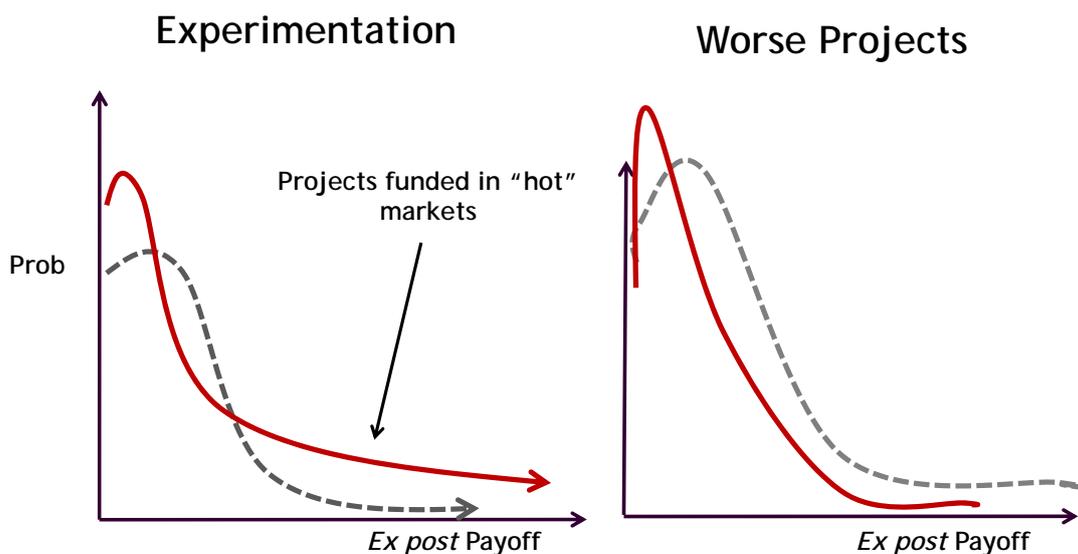


Figure 1: Distinguishing Risky Investments from Worse Investments by looking at the ex post distribution of outcomes

The main objective of this paper is therefore to examine the extent to which the pattern of VC investments in boom times looks more like the chart on the left, as opposed to the chart on the right. Our analysis has two main elements. First, we document a robust correlation between firms being funded in boom times being simultaneously less likely to IPO but having bigger successes in the fewer instances when they do IPO. We also show that the bigger successes are not just limited to a financial measure of valuation, but also extend to real outcomes such as the level of a firm's patenting. This suggests that VCs also invest in more innovative firms in boom times.

The second element of our analysis entails an initial look at the mechanism behind this correlation. VC investments clearly follow investment opportunities, so that investment opportunities associated with new technologies and markets are likely to be riskier and also attract more VC money. However, there is also a possibility that in addition to this, the flood of money during boom times allows VCs to experiment more effectively, and thereby change the type of investments they choose to make towards more novel, innovative startups. We

examine the extent to which this second mechanism of “money *changing* deals” may also be at play, by using instrumental variables to untangle the endogeneity in the analysis.

Before proceeding with the results, we first outline the data used in our analysis in Section III. below.

III. Data

The core of our analyses are based on data from Thompson Venture Economics.² This dataset forms the basis of studies by the National Venture Capital Association in the US, as well as most academic papers on venture capital. We focus our analysis on US based startups, since data for these firms is most comprehensive. The US is also a good setting for our study because the institutionalization of the venture industry in the US implies that startups backed by venture capital firms are likely to comprise the majority of startups that commercialize new technologies in the US.

We focus our analysis on startups whose first financing event was an early stage (Seed or Series A) investment from 1980 onwards. This allows us to follow them to see their eventual outcome. Given that we are interested in following the firms until they exit, we truncate the sample in 2004 to allow ourselves sufficient time for firms that were first financed in 2004 to IPO. We therefore focus our analysis on startups receiving their initial early stage investment over the twenty five year period from 1980 to 2004, but follow these firm’s eventual outcomes until the end of 2010.

As can be seen from Table 1, there are 14,667 firms that meet our criteria of US-based startups that received their first early stage financing between 1980 and 2004. The probability that the firm has an IPO is 10% in the overall sample, but varies from 7% for Internet and Software startups to 19% for startups in the biotechnology and health care sectors.

²This dataset was formerly known as VentureXpert.

As noted in Section II. above, a key way of distinguishing whether worse firms or riskier firms are being funded in hot markets is that their *ex post* distribution of outcomes is different. That is, although both risky and worse investments will lead to fewer successes (and hence a lower probability of an IPO in the context of our sample), risky investments would imply that conditional on an IPO, firms funded in hot markets will have a higher economic return than those funded in cold markets. On the other hand, worse investments would imply that even conditional on an IPO, firms funded in hot markets had lower value than those funded in cold markets. In order to examine this claim, a key measure we use is the pre-money valuation at IPO for firms that eventually had an IPO.³ This data was collected from SDC's IPO database and when missing, directly from firms' SEC filings. As can be seen from Table 1, the average pre-money valuation for a firm in our sample that had an IPO was \$200 M. However, this varied from over \$300 M for Internet and Communications startups to just over \$ 100 M for biotechnology and health care startups.

In order to determine whether the bigger successes were purely financial or also present in 'real outcomes', we also examine two measures of firm innovation. The first is a raw count of patents granted to the firm that were filed in the 3 years following its *first funding*. The second measure is the cumulative number of citations to these patents, up to three years from the patents being granted.⁴ Both these measures were collected by hand-matching the names of the firms that IPOed to assignees in the US Patent and Trademark Office (USPTO) patent database maintained by the NBER. This data set has patent-level records with information on the filing and grant dates for all patents in the US as well as information on citations to prior art made by each patent. Matching firms in our sample to the patent database therefore

³Note that the pre-money valuation is the value of the firm before accounting for the new money coming into the firm at the IPO. Since firms will raise different amounts of money in the IPO, the pre-money allows a more clear-cut comparison of value across firms.

⁴While the three year windows are somewhat arbitrary, they are chosen so as to minimize the number of years that would be dropped from the analysis (given about a 2-3 year delay in the granting of patents from the time they are filed).

allows us to calculate their patenting in the 3 years immediately following their first funding and the subsequent citations those patents received in the three years following their grant. This facilitates the study of the innovations by the startups while they were still private. As can be seen from Table 1, the average number of patents filed is 3.7 and the average number of citations is 16.5, but there is again significant variation in both patenting and citation rates across industry sectors.

In Table 2, we provide descriptive statistics that show the main patterns in the data. The descriptive statistics highlight the basic pattern we test in the following section. We find that startups funded in ‘hot’ quarters were less likely to IPO, despite raising more money in their first round of funding. Successful firms funded in hot markets raise more money prior to their IPO, and interestingly, take almost the same time from first funding to IPO. Conditional on going public, however, firms funded in ‘hot’ markets are valued more on the day of the IPO and have more patents and citations to their patents.

IV. Regression Results

A. Riskier investments or Worse Investments?

In Tables 3 and 4, we turn to firm-level regressions to examine the relationship between the financing environment in a the quarter a firm received its first financing, and the ultimate outcome for that firm. Table 3 reports estimates from OLS regressions where the dependent variable is binary and takes the value 1 if the firm had an IPO.⁵ The estimations take the form:

$$Y_i = \beta_1 OTHFIN_t + \beta_2 X_i + \phi_j + \tau_T + \varepsilon_i \quad (1)$$

⁵We have reported the results from OLS regressions, in order to facilitate comparisons with the IV regressions in following tables. The results are robust to running the regressions as probit models.

In these regressions, each observation corresponds to an individual entrepreneurial firm and the dependent variable, Y_i refers to the eventual outcome for firm i . It takes the value 1 if the firm had an IPO and zero otherwise. ϕ_j , refers to industry-level fixed effects, corresponding to the five industries outlined in Table 1. τ_T refers to period fixed effects. Since our hypothesis is about the cyclicity of investment over time, we cannot absorb all the inter-temporal variation in our data by including quarter-level or annual fixed effects. However, given that our sample spans 25 years, we also want to ensure that we do include some period controls to account for systematic changes in the size of funds as the industry matured. We therefore segment the data into three periods, corresponding to 1980-1989, 1990-1999 and 2000-2004. Period fixed effects refer to dummy variables for these three periods.

The variable $OTHFIN_t$ is our main variable of interest and refers to the number of other firms in the sample that received their initial early stage financing in the same quarter as firm i . It therefore captures the level of financing activity in the quarter that the focal firm was first funded, and proxies for the extent to which a given quarter was “hot” in that period. The matrix X_i refers to firm-level covariates that we include in the regressions. These include the amount of money the startup raised in the financing event, the number of investors in the syndicate that made the investment, and dummy variables to control for whether the startup was based in California or Massachusetts. Standard errors are clustered by quarter to account for the fact that our main outcome of interest is measured at the quarterly-level.

As can be seen from Table 3, firms that were first financed in quarters with a lot of financing activity were less likely to IPO. The results continue to be robust to the inclusion of firm-level covariates, industry fixed effects and period fixed effects. In addition, in column (5) we drop the quarters associated with the extreme spike in activity during the internet bubble to ensure that the results were not being driven by these outliers. $OTHFIN_t$ is measured in terms of 100s of firms, so the magnitude of the coefficients in column (4) (with industry and period

fixed effects and all controls) imply that an increase in the number of early stage investments in a given quarter by 100 is associated with a 1.6% fall in the probability of an IPO. Given the baseline IPO probability is 10%, and the standard deviation of investments per quarter is 135, this implies that a one standard deviation increase in the number of investments per quarter is associated with a 20% fall in the probability that any one of those investments goes public. Table 3 therefore highlights the fact that firms financed in boom times are less likely to IPO. In Appendix 1 we also find that firms funded in boom times are more likely to go bankrupt. These results, however, do not imply that VCs fund more ‘junk’ in hot markets. In order to make this inference, we also need to examine the degree of success for the firms that IPO.

In Table 4, we report estimates from firm-level regressions where the dependent variable is the log of the pre-money value for the firm, conditional on it eventually going public. That is, for the 10% of firms in our sample that did eventually go public, we run regressions that take the form:

$$\log(PREVAL)_i = \beta_1 OTHFIN_t + \beta_2 X_i + \phi_j + \tau_T + \varepsilon_i \quad (2)$$

As with Table 3, each observation in these regressions corresponds to an individual firm and the dependent variable, $\log(PREVAL)_i$ refers to the premoney value for the firm on the day it went public. Again, our main variable of interest is $OTHFIN_t$, that measures the number of firms in our original sample that were first financed in the same quarter as firm i . The matrix X_i refers to firm-level covariates that we include in the regression. These include the logged total amount of money raised prior to the IPO, the logged value of the NASDAQ on the day of the IPO, and dummy variables to control for whether the startup was based in California or Massachusetts. As before, standard errors are clustered at the quarter-level.

An important aspect of these regressions is that we want to ensure that our results are not simply due to the fact that firms funded in hot times to public at different times and hence

face a systematically different threshold of going public. In order to address this concern, we include IPO-year fixed effects in our regressions. That is, for firms that had an IPO in the same year, we look at whether those funded in hot markets were likely to have bigger premoney values, controlling for the amount of money they raised.

As can be seen from Table 4, conditional on going public and controlling for the year in which they IPO, firms funded in quarters with a lot of funding activity have a higher valuation on the day of their IPO. This result is robust to controlling for the value of the NASDAQ on the day of the IPO, as well as the amount of money raised by the firm till that point. The coefficient on column (4) (with industry and IPO year fixed effects and all controls) implies that a one standard deviation increase in the funding activity in a given quarter is associated with a 7%, or \$ 15 million increase in the value of a firm (from \$208 M to \$223 M) if it goes public.

Our results suggest that VCs fund riskier firms in quarters with more financing activity. Although these firms have a lower probability of going public, *conditional* on an IPO, they are more valuable.

B. Investor Fixed Effects

In Table 5, we examine whether the correlations we are observing are driven by different investors who might be entering during periods of high financing activity, or whether the same investors make riskier investments during hot markets. In order to do so, we run the same regressions as outlined in Tables 3 and 4, but at the investor-firm level. That is, we now have multiple observations for firms with more than one investor in the syndicate. In these instances, each observation corresponds to the specific investor-firm pair in that round of funding, so that Y_i becomes Y_{ik} and $\log(PREVAL)_i$ becomes $\log(PREVAL)_{ik}$.

Expanding the data to the investor level allows us to include investor fixed effects, and thereby examine whether the same investors themselves change the types of firms they fund in hot and cold markets. Specifically, Table 5 reports results from estimations that take the form:

$$Y_{ik} = \beta_1 OTHFIN_t + \beta_2 X_i + \phi_j + \psi_k + \tau_T + \varepsilon_{ik} \quad (3)$$

and

$$\log(PREV AL)_{ik} = \beta_1 OTHFIN_t + \beta_2 X_i + \phi_j + \psi_k + \tau_T + \varepsilon_{ik} \quad (4)$$

where ψ_k refers to investor fixed effects and all the other variables are exactly as defined in Tables 3 and 4.

Table 5 reports these estimates for all firms in the sample for whom we have a unique identifier and who had multiple investments. In column (2) and (4) we also reduce the set of investors to the most experienced firms which includes only the firms that made at least 25 investments over the period 1980-2004. As can be seen from Table 5, the patterns observed in Tables 3 and 4 continue to hold, with very similar magnitudes.⁶ These findings are important as they highlight the observed relationship between hot markets and risky firms seems to come from within-firm changes in the type of investments made across the cycle, as opposed to a different types of investors investing in risky vs. less risky firms across the cycle. Moreover, even the most active/experienced investors shift the the level of risk in their investments across the cycle.

C. Money *Changing* Deals?

One likely explanation for our results is that venture capital investments will be particularly high at times when risky technologies, ideas and startups are available to be financed. The

⁶Appendix 2 shows that the same pattern holds for the probability of failure as in Appendix 1.

arrival of new technologies attracts investment and these new technologies are more likely to be risky investments. In addition to this explanation, however, Nanda and Rhodes-Kropf (2011) provide a theoretical model linking financial market activity to more risky investments. In their model, the increase in financing activity also lowers financing risk, which allows investors to experiment more effectively, and hence take on riskier, more innovative investments. According to this view, the flood of money associated with the presence of heated investment activity may actually cause VCs to change the type of investments they are willing to make – towards more risky, innovative startups in the market.

In order to examine the extent to which this second mechanism is also at play, we exploit a particular feature of the venture industry, which is that the investors in venture capital funds (the limited partners) tend to allocate capital to the private equity asset class as a whole. This leads fundraising by venture and buyout funds to be associated. Our assumption (for the exclusion restriction to be satisfied) is that limited partner decisions to allocate to buyout funds are uncorrelated with the opportunity set in venture capital. This seems reasonable since buyout funds focus on turnarounds of existing companies while early stage investors focus on new technologies and opportunities. If so, our instrumental variables approach should capture that part of the investments that are due to changes in capital availability that are unrelated to the investment opportunities available at the time for venture capital funds. Lagged buyout fundraising is used as an instrument to further remove the instrument from current VC opportunities and to account for the fact that venture funds take 1-3 years to fully invest the capital in their funds.

We therefore run two-stage-least-squares regressions, where the variable $OTHFIN_t$ in equations (1) and (2) is treated as endogenous and a variable that calculates the number of buyout funds closed 5-8 quarters before t is used to instrument for $OTHFIN_t$. These results are reported in Table 6 columns (2) and (4). In columns (1) and (3) we report the coefficients from

comparable OLS regressions for easy comparison. As can be seen from the bottom of Table 6, the regressions have a strong first stage, and pass the F-test for possible weak instruments.

The magnitudes of the IV results move in a particular direction that highlight the nature of the endogeneity present. Comparing column (1) to column (2) in Table 6 we see that the coefficients on the IV are more negative than the OLS. This implies that increased capital makes firms less likely to IPO, and furthermore that this relationship is stronger than that due to an increase in the number of investments.⁷ At the same time, comparing columns (3) and columns (4) of Table 6 we see that the IV coefficients are more positive than the OLS implying that conditional on going public, increased capital increases the premoney value at the time of the IPO, and again more so than just an increase in the number of investments. That is, IV regressions accentuate our finding that risky firms are funded when capital is abundant. In line with the findings in other work, they suggest that active investing times are also times when investment opportunities are better. These better investment opportunities may, on average, have a higher likelihood of going public at a good valuation. Increased capital, however, pushes investors to make riskier investments. They are more likely to fail, but if they succeed, they can be even more valuable than good, but less risky investments. This is the why the IV coefficients are both more negative and more positive than their respective OLS coefficients.

In Table 7, we report the result of the same regressions, but run at the investor-firm level and including investor fixed effects. The results continue to hold, implying that the high level of investment activity leads VCs to change the type of investments that they make, towards more risky startups that may have a higher probability of failure, but may also have bigger successes.

These are fascinating results because they imply a much larger role for financial markets in the innovative process than previously thought. Rather than money simply flowing toward

⁷Appendix 2 also shows that increased capital makes firms more likely to fail, and this relationship is stronger than that due to an increase in the number of investments.

good ideas and away from bad, the results in Tables 6 and 7 imply that a flood of money into the venture community can actually increase the riskiness of the projects funded. The question then is, is this just a shift to riskier projects or actually to more innovative ones?

D. “Risky” vs “Novel” Investments

Thus far, the results we have reported in Tables 3-7 are based on financial measures of success. That is, firms funded in hot markets are less likely to IPO (and more likely to fail), but are valued higher on the day of their IPO. In Tables 8 and 9, we extend the estimation framework we used to study valuation to real outcomes associated with firm-level innovation. That is, we ask whether these are purely more risky investments in financial terms or whether the investments VCs make in hot markets are associated with more novel technologies, or innovative firms.

Following a long literature in economics (for example Jaffe et al. (1993)), we use firm-level patenting as our measure of innovation. While patenting is only one measure of firm-innovation, it is a very relevant measure of innovation in our sample of high-tech firms. Over two-thirds of the firms that IPOed filed at least one patent in the three years following their first investment. Moreover, patent citations have been shown to correlate closely with both the quality of inventions as well as their economic effects (Hall et al. (2005)).

In Tables 8 and 9, we re-run the estimations reported in Tables 6 and 7, but with the number of patents and number patent citations as the dependent variable. Table 8 shows that firms funded in hot markets had a 20% higher rate of patenting, and that there was weak evidence that these patents were also more highly cited. In Table 9, we include investor fixed effects and report the estimates for the most active investors, who made at least 25 investments in our sample period. The results of these regressions are significantly stronger, suggesting that the most experienced investors are particularly likely to change their investments towards more novel, innovative startups in periods of high financing activity.

Consistent with our finding in previous tables, our coefficients on the IV are higher than the comparable OLS coefficients. This suggests that increased capital leads to more novel investments and this relationship is stronger than that due to increases in the number of investments.⁸

V. Conclusions

New firms that surround the creation and commercialization of new technologies have the potential to have profound effects on the economy (Aghion and Howitt (1992), Foster et al. (2008)). The creation of these new firms and their funding is highly cyclical (Gompers et al. (2008)). Conventional wisdom associates the top of these cycles either with negative attributes (a left shift in the distribution of projects) or with better investment opportunities (a right shift in the distribution of projects).

However, the evidence in our paper suggests another, possibly simultaneous, phenomenon. We find that firms that are funded in ‘hot’ times are more likely to fail but simultaneously create more value if they succeed. This pattern of a “twist” in the distribution of outcomes (rather than simply a shift) could arise if more novel firms are funded in hot times. Our results provide a new but intuitive way to think about the differences in project choice across the investment cycle. Since the financial results we present cannot distinguish between more innovative versus simply riskier investments, we also present direct evidence on level of patenting by firms funded at different times in the cycle. Our results suggest that in addition to being valued higher on the day of their IPO, successful firms that are funded in hot markets had more patents and received more citations in the initial years following their first funding than firms funded in less heady times.

⁸i.e. the portion of the investments that are unrelated to lagged buyout fundraising activity are less related to patenting and patent citations.

Our IV results suggest that part of these findings may be driven by the fact that potentially new inventions cause the arrival of more funding and create a ‘hot’ environment. However they also highlight that changes capital that are unrelated to the investment opportunities seem to exacerbate our results, suggesting that one of the attributes of hot markets is that it makes investors more willing to experiment and thereby fund novel investments. This finding is consistent with Nanda and Rhodes-Kropf (2011), who demonstrate how increased funding in the venture capital market can actually rationally alter the type of investments investors are willing to fund toward a more experimental, innovative project. According to this view, the abundance of capital associated with investment cycles may not just be a response to the arrival of new technologies, but may in fact play a critical role in driving the creation of new technologies. That is, the abundance of capital may change the type of firm investors are willing to finance in these times. Financial market investment cycles may therefore create innovation cycles.

Our findings suggest many avenues for future research which consider the impact of the cycle on innovation, venture capital and the development of new companies. Many of the classic findings in venture capital could be extended to examine how they are impacted by the cycle. For example, the interaction of product markets and firm strategy (Hellmann and Puri (2000)), persistence (Kaplan and Schoar (2005)), grandstanding (Gompers (1996)), the effect of networks (Hochberg et al. (2007)), or the question of the jockey or the horse (Kaplan et al. (2009)), all may depend on the cycle in a fascinating way.

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Table I

Descriptive Statistics

This table reports descriptive statistics on US based startups who received Seed or Early Stage financing from an investor in the Venture Economics database between 1980 and 2004. For these firms, we report data on the first financing event and the ultimate outcome of the startup as of December 2010

	Number of Firms	Share with IPO	Average Pre-Money Valuation if had an IPO (\$, MM)	Patenting	Citations to Patents
Full Dataset	14,667	10%	208	3.7	16.5
Biotechnology and Healthcare	2,601	19%	115	5.4	20.8
Communications and Media	1,631	11%	324	3.4	18.2
Computer Hardware and Electronics	2,067	11%	195	4.7	21.9
Internet and Computer Software	6,050	7%	315	2.2	12.3
Non-High Technology	2,318	8%	123	1.7	6.6

Table II
Characteristics of Startups Funded in Hot vs. Cold Periods

This table reports differences in the characteristics of firms that receive their *first funding* in hot vs. cold periods. Hot periods are defined as being in the top third of quarters in terms of startups being funded in each of the periods 1980-1989, 1990-1999 and 2000-2004.

	All	Funded in Hot Periods	Funded in Cold Periods	P Value for Two-Tailed Test
<u>All Firms in the Sample</u>				
Number of quarters	100	32	68	
Number of firms funded per quarter	147	262	93	<0.001***
Dollars invested in first funding	\$ 4.2 M	\$5.0	\$3.2	<0.001***
Startup based in California	37%	38%	36%	0.137
Startup based in Massachusetts	11%	11%	11%	0.974
Share of startups that had an IPO	10%	8%	14%	<0.001***
<u>Firms that had an IPO</u>				
Firm age at IPO	4.7	4.7	4.8	0.762
Total Dollars raised prior to IPO	\$42	\$47	\$37	<0.001***
Average Pre-Money Value at IPO	\$ 208 M	\$ 287 M	\$ 152 M	<0.001***
Number of patents in 3 years following first funding	3.7	4.3	3.2	0.007**
Citations to patents in 3 years following first funding	16.5	18.6	13.3	0.055*

Table III
Probability of IPO based on market when the startup received first funding

This table reports the probability of a startup being coded as having an IPO" based on the characteristics of the VC funding environment when it first received funding. All regressions are OLS regressions where the dependent variable takes a value of 1 if the startup had an IPO and zero otherwise. The results are robust to using Probit regressions, but coefficients from OLS specifications are reported to facilitate comparisons with the IV regressions in later tables. Industry Fixed Effects control for the 5 industries outlined in Table 1. Period Fixed effects control for the startup being funded in the period 1980-89, 1990-99 or 2000-2004. Standard errors are clustered by quarter.

	1980-2004					Drop 98-'00
	(1)	(2)	(3)	(4)	(5)	
No. of other firms financed in that quarter	-0.027*** (0.003)	-0.028*** (0.003)	-0.026*** (0.003)	-0.016*** (0.005)	-0.046*** (0.012)	
\$ raised in first financing		0.007** (0.003)	0.008*** (0.003)	0.016*** (0.003)	0.020*** (0.003)	
Number of investors in syndicate		0.013*** (0.002)	0.012*** (0.002)	0.009*** (0.002)	0.012*** (0.003)	
Startup based in California		0.026*** (0.007)	0.025*** (0.007)	0.023*** (0.006)	0.033*** (0.009)	
Startup based in Massachusetts		0.013 (0.010)	0.010 (0.010)	0.007 (0.010)	0.010 (0.013)	
Industry Fixed Effects	No	No	Yes	Yes	Yes	Yes
Period Fixed Effects	No	No	No	Yes	Yes	Yes
Number of observations	14,667	13,903	13,903	13,903	13,903	8,896
R-Squared	0.03	0.04	0.06	0.08	0.08	0.08

Table IV
Pre-Money Valuation at IPO based on when Startup received first funding

This table reports the results from regressions looking at the value of firms that had an IPO, based on the quarter in which they received their first funding. Coefficients in the table are from OLS specifications where the dependent variable is the log of the pre-money valuation on the day the firm IPO'ed. Industry Fixed Effects control for the 5 industries outlined in Table 1. IPO-year fixed effects control for the year in which the startup had its IPO. Standard errors are clustered by quarter.

	1980-2004					Drop 1998-2000
	(1)	(2)	(3)	(4)	(5)	
No. of other firms financed in that quarter	0.297*** (0.050)	0.056** (0.022)	0.076*** (0.026)	0.050* (0.026)	0.076* (0.041)	
Total \$ raised prior to IPO		0.299*** (0.027)	0.303*** (0.027)	0.317*** (0.026)	0.320*** (0.027)	
Value of NASDAQ on day of IPO		0.400*** (0.042)	0.268 (0.275)	0.274 (0.284)	0.193 (0.312)	
Startup based in California		0.209*** (0.064)	0.186*** (0.059)	0.162** (0.062)	0.158** (0.064)	
Startup based in Massachusetts		0.125 (0.077)	0.129* (0.075)	0.106 (0.074)	0.055 (0.068)	
IPO year Fixed Effects	No	No	Yes	Yes	Yes	Yes
Industry Fixed Effects	No	No	No	Yes	Yes	Yes
Number of observations	1,455	1,455	1,455	1,455	1,455	1,242
R-Squared	0.11	0.42	0.42	0.41	0.41	0.41

Table V
Funding Environment and Startup Outcome - Investor Fixed Effects

This table OLS regressions as in Tables III and IV, but includes multiple observations per startup firm to account for multiple investors in the initial round of funding. This allows the presence of investor fixed effects. We report two sets of specifications. The first includes all firms for which we have data on the identity of the investors. The second reports only the most experienced investors, who make at least 25 investments over the period 1980-2004. Time controls refer to period fixed effects in columns(1) and (2) and to IPO-year fixed effects in columns (3) and (4). Control variables, industry, period and IPO-year fixed effects are exactly the same as in Tables III and IV. Standard errors are clustered by quarter.

	Probability of IPO				Pre-Money Value conditional on IPO			
	All Investors	Investors >= 25 investments	All VCs	VCs >= 25 investments	All Investors	Investors >= 25 investments	All VCs	VCs >= 25 investments
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
No. of other firms financed in that quarter	-0.019*** (0.005)	-0.024*** (0.006)	0.065* (0.039)	0.076* (0.040)	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Investor Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.20	0.12	0.61	0.52				
Number of observations	25,314	13,940	3,264	2,184				

Table VI
The Effect of Increased Capital at time of funding on Startup Outcomes

This table reports the results of 2 stage least square regressions, where the number of other firms financed in a given quarter is instrumented with a variable that measures the number of leveraged buyout funds that were raised in the 5-8 quarters before the firm was funded. Limited partners tend to allocate capital to the "private equity" asset class as a whole -- leading fundraising by venture and buyout funds to be associated. Our assumption is that limited partner decisions to allocate capital to buyout funds are unrelated to the opportunity set in venture capital. Hence, our instrument should capture that part of the investments that are due to increases in capital that are unrelated to the investment opportunities for venture capital funds. Lagged buyout fundraising is used as an instrument to account for the fact that venture funds take 1-3 years to fully invest the capital in their funds and to further distance the instrument from current VC opportunities. Time Fixed Effects refer to Period Fixed effects in columns (1) and (2) and to IPO-year fixed effects for columns (3) and (4). Control variables and fixed effects are as reported in Tables III and IV. Standard errors are clustered by quarter.

	Probability of IPO				Pre-Money Value conditional on IPO	
	OLS (Reg (4) in Table III)	IV	IV	OLS (Reg (4) in Table IV)	IV	IV
No. of other firms financed in that quarter	(1)	(2)	(3)	(4)		
	-0.016*** (0.005)	-0.023*** (0.007)	0.050* (0.026)	0.182* (0.101)		
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.08	0.04	0.41	0.32		
Number of observations	13,903	13,903	1,455	1,455		
<i>Coefficient on Instrument and First Stage Statistics</i>						
Number of buyout funds closed 5-8 Quarters before		0.053*** (0.012)		0.024*** (0.007)		
Partial R-squared		0.243		0.076		
F-Statistic		21.02		10.54		

Table VII
The Effect of Increased Capital at time of funding on Startup Outcomes - Investor Fixed Effects

This table reports the same regressions as in Tables V, but focusing on investors with at least 25 investments over the period 1980-2004. As with Table VI, the number of other firms financed in the quarter the firm received its first funding is instrumented with the number of buyout funds raised 5-8 quarters before. Time fixed effects refer to period fixed effects in columns (1) and (2) and to IPO-year fixed effects in columns (3) and (4). Control variables and fixed effects are as reported in Table V. Standard errors are clustered by quarter

	Probability of IPO		Pre-Money Value conditional on IPO	
	OLS (Reg (2) in TableV)	IV	OLS (Reg (4) in TableV)	IV
No. of other firms financed in that quarter	(1) -0.024*** (0.006)	(2) -0.037*** (0.004)	(3) 0.076* (0.040)	(4) 0.204** (0.095)
Control Variables	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Investor Fixed Effects	Yes	Yes	Yes	Yes
R-Squared	0.06	0.06	0.52	0.50
Number of observations	13,940	13,940	2,184	2,184
<i>Coefficient on Instrument and First Stage Statistics</i>				
Number of buyout funds closed 5-8 Quarters before		0.043*** (0.010)		0.016** (0.006)
Partial R-squared		0.220		0.083
F-Statistic		19.22		23.53

Table VIII
Funding Environment and Startup Innovation

This table reports the coefficients from OLS and IV regressions looking at the patenting activity of firms after their first funding. In order to remain consistent with the 1980-2004 funding period, we examine patents filed in the three years following first funding and the cumulative citations to those patents upto three from the date the patent was granted. Control variables, fixed effects and instrumental variables are same as those reported in Table VI. Standard errors are clustered by period.

	Patents filed in 3 years following first funding		Citations to patents filed in 3 years following first funding	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
No. of other firms financed in that quarter	0.071*** (0.021)	0.105* (0.059)	0.070* (0.039)	0.063 (0.088)
Control Variables	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Period Fixed Effects	Yes	Yes	Yes	Yes
R-squared	0.18	0.17	0.15	0.15
Number of observations	1,477	1,477	1,477	1,477
<i>Coefficient on Instrument and First Stage Statistics</i>				
Number of buyout funds closed 5-8 Quarters before		0.027*** (0.008)		0.027*** (0.008)
Partial R-squared		0.147		0.147
F-Statistic		12.85		12.85

Table IX
Funding Environment and Startup Innovation - Investor Fixed Effects

This table reports the same regressions as in Tables VIII, but including investor fixed effects for the sample of firms with at least 25 investments over the period 1980-2004. Control variables, fixed effects and instrumental variables are as in Table VII with the additional inclusion of investor fixed effects. Standard errors are clustered by quarter

	Patents filed in 3 years following first funding		Citations to patents filed in 3 years following first funding	
	OLS (1)	IV (2)	OLS (3)	IV (4)
No. of other firms financed in that quarter	0.096*** (0.030)	0.202*** (0.054)	0.117** (0.054)	0.159* (0.084)
Control Variables	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Period Fixed Effects	Yes	Yes	Yes	Yes
Investor Fixed Effects	Yes	Yes	Yes	Yes
R-Squared	0.33	0.28	0.31	0.28
Number of observations	3,011	3,011	3,011	3,011
<i>Coefficient on Instrument and First Stage Statistics</i>				
Number of buyout funds closed 5-8 Quarters before		0.022*** (0.001)		0.022*** (0.001)
Partial R-squared		0.126		0.126
F-Statistic		11.1		11.1

Appendix 1
Probability of failure based on market when the startup received first funding

This table reports the probability of a startup being coded as "bankrupt" based on the characteristics of the VC funding environment when it first received funding

	1980-2004				Drop 98-'00
	(1)	(2)	(3)	(4)	(5)
No. of other firms financed in that quarter	0.016*** (0.003)	0.021*** (0.003)	0.019*** (0.003)	0.034*** (0.003)	0.025* (0.015)
\$ raised in first financing		-0.019*** (0.004)	-0.020*** (0.003)	-0.008*** (0.003)	-0.012*** (0.003)
Number of investors in syndicate		0.004 (0.002)	0.005** (0.002)	-0.002 (0.002)	0.001 (0.002)
Startup based in California		0.030*** (0.009)	0.031*** (0.009)	0.031*** (0.009)	0.020** (0.009)
Startup based in Massachusetts		-0.002 (0.011)	0.001 (0.011)	-0.004 (0.010)	-0.001 (0.010)
Industry Fixed Effects	No	No	Yes	Yes	Yes
Period Fixed Effects	No	No	No	Yes	Yes
Number of observations	13,903	13,903	13,903	13,903	8,896
R-Squared	0.04	0.04	0.06	0.08	0.08

Appendix 2
Probability of Failure - Investor Fixed Effects

This table reports the same regressions as in Tables III, IV and V, but focusing on investors with at least 25 investments over the period 1980-2004.

	Probability of Failure				Probability of Failure: Investor Fixed Effects for investors with >= 25 investments			
	OLS	IV	IV	OLS	OLS	IV	IV	OLS
No. of other firms financed in that quarter	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	0.034*** (0.003)	0.047*** (0.008)	0.033*** (0.002)	0.051*** (0.004)	0.034*** (0.003)	0.047*** (0.008)	0.033*** (0.002)	0.051*** (0.004)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Investor Fixed Effects	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
R-Squared	0.06	0.06	0.52	0.50	0.06	0.06	0.52	0.50
Number of observations	13,903	13,903	13,940	13,940	13,903	13,903	13,940	13,940
<i>Coefficient on Instrument and First Stage Statistics</i>								
Number of buyout funds closed 5-8 Quarters before		0.053*** (0.012)		0.043*** (0.010)		0.053*** (0.012)		0.043*** (0.010)
Partial R-squared		0.243		0.220		0.243		0.220
F-Statistic		21.02		19.22		21.02		19.22