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ABSTRACT

Despite theoretical predictions to the contrary, corporate innovation is strongly pro-cyclical. In this paper, we compare innovation in the economy as a whole to that of firms backed by venture capital (VC), a source of capital associated with the most impactful young firms. We show that (1) patents filed by VC-backed firms are of significantly higher quality and economic importance than those in the broader economy, (2) venture-backed innovation is even more procyclical than innovation in general, and (3) that the deterioration of venture innovation in downturns appears driven by shifts in the types of startups that these investors finance. Our findings suggest that during recessions, venture capitalists perceive a need to conserve capital both due to demand for financing from struggling companies already in their portfolios and due to a more challenging fundraising environment. Therefore, they shift funding to less innovative firms that are closer to profitability. Rather than countering the pro-cyclicality of innovation in the broader economy, VC finance appears instead to amplify this pattern.

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1 Introduction

The cyclical nature of innovation has long been puzzling. On the one hand, a large body of theory predicts that high-quality innovation should be counter-cyclical, for example, if creative destruction occurs during recessions (Schumpeter 1939; Hall 1991; Caballero and Hammour 1994; Aghion et al. 2012). One rationale is that the opportunity cost of investing in future productivity growth is lower during recessions, creating incentives for innovative activity (Cooper and Haltiwanger 1993; Aghion and Saint-Paul 1998). On the other hand, a large empirical literature, beginning with Griliches (1984), documents that innovation is pro-cyclical, a fact that we confirm and extend using long-horizon patent data (Figure 1). Existing work on firm-level procyclicality has primarily relied on mid-twentieth century data and focused on publicly traded firms.

In recent years, there has been increasing attention to the role of young, private firms in driving innovation. This shift reflects the declines in basic research and in research efficiency at large corporations, which have traditionally accounted for the bulk of R&D expenditures (Bloom et al. 2020; Arora, Belenzon, and Sheer 2021). In addition, evidence that young, private firms are disproportionately responsible for new products and job creation (Decker et al. 2014; Acemoglu et al. 2018). Venture capital (VC) is perhaps the most important source of financing for such firms. VC has been shown to be a key source of innovation (Kortum and Lerner 2000; Gornall and Strebulaev 2015), and is growing in volume; in 2021, for instance, $345 billion was invested in U.S. venture deals, while U.S. R&D expenditures were $792 billion.[1]. Despite the growing academic and policy interest in VC, we know little about how venture-backed innovation varies over the business cycle and how this relates to innovation in the broader economy.

In this paper, we explore—to our knowledge for the first time—the relative contribution of VC to the procyclicality of innovation. On the one hand, VC is

[1] https://nvca.org/wp-content/uploads/2023/03/NVCA-2023-Yearbook_FINALFINAL.pdf and https://ncses.nsf.gov/data-collections/national-patterns/2021#survey-info

well-suited to be an instrument of Schumpeterian creative destruction, given these investors' taste for risk and its long-term structure that locks away funds for about ten years (Lerner and Nanda 2020). These factors might make VC-backed innovation relatively stronger during downturns. Anecdotally, many innovative firms backed by venture funds were founded during recessions, ranging from Microsoft in 1975 to iRobot in 1990 to Uber, Slack, and Airbnb in 2008-09.

On the other hand, VC-backed innovation might decline during downturns. This could reflect supply considerations if entrepreneurs propose less risky and innovative ideas during recessions. Alternatively, it could reflect changing demand if venture investors face more financing constraints during recessions, either because they must conserve capital for existing portfolio companies or because fundraising from their limited partner investors becomes more challenging.

In this paper, we take a first step towards addressing this gap, by empirically exploring shifts in VC investment during recessions and the role this might have on the nature of VC-backed innovation. We examine whether the volume and quality of VC-backed innovation are higher or lower during recessions, and the potential reasons for these patterns. To shed light on these questions, we use data on VC financing matched to the patenting of VC-backed startups over the period from 1976 to 2017. An important difference in our analysis from most prior work on VC and innovation is that we examine all U.S. patents, thereby comparing innovation among VC-backed firms to innovation conducted more broadly in the economy. Our study of how VC-backed innovation has evolved relative to the broader economy over macro-economic cycles in this time period reveals three key patterns.

First, patents filed by VC-backed startups are of higher quality and economic importance than the average patent. Citation counts provide one indicator. For instance, 22% of the VC-backed patents are in the top 10% of most-cited patents (defined relative to all patents whose applications were filed in the same month), and 2.9% are in the top 1% most highly-cited patents. VC-backed firms are also disproportionately likely to have more original patents, more general patents, and patents more closely related to fundamental science. This finding is consistent with VC-backed firms playing a disproportionately important role in terms of job creation and productivity growth (Puri and Zarutskie 2012; Akcigit et al. forthcoming).

Second, we find that VC-backed innovation is pro-cyclical, and even more so than the broader economy. Specifically, relative to all other patent filings within a technology class, the number of patents applied for by VC-backed firms, as well as the quality of those patents, declines during recessions. Patent activity among VC-backed firms is also positively correlated with the amount of VC investment into startups in a given month. Even after controlling for the lower amount of VC finance available to startups in recessions, we find that recession periods are associated with particularly low levels and quality of innovation.

Third, we trace the cyclicality of VC-backed innovation to innovation being conducted by *early-stage* startups. The higher likelihood of VC-backed startups having patents in the upper tail of novelty and impact during normal times is more pronounced for patents filed by startups whose most recent round of financing was a Seed or Series A investment, as opposed to Series B, C, etc. The disproportionate declines in novelty and impact of VC-backed startups during recessions are also due to early stage startups. Conversely, startups that most recently received late-stage VC investments exhibit no significant differences in innovation over the business cycle relative to innovation being conducted across the broader economy.[2]

Thus, rather than being insulated from downturns as a common narrative suggests, venture-backed firms appear particularly sensitive to these cycles. Potential mechanisms can be grouped into two broad categories. One is that investment opportunities for venture investors are more cyclical relative to the broader economy. This is no doubt a

[2]The fact that late-stage VC appears to be more insulated from the public markets is consistent with Bernstein, Lerner, and Mezzanotti (2019), who find that investment at private equity-funded companies was less sensitive to the 2008 financial crisis.

factor, at least during particular recessions. A second mechanism is that venture capitalists' willingness to fund more novel innovation may decline during recessions. We find substantial support for this channel in our data. Venture investors appear to delay new investments, particularly into more risky or novel investments, when faced with uncertainty or due to anticipated constraints in the capacity to deploy capital. We find that the decline in innovation among early-stage startups during recessions is driven by venture capitalists financing less innovative firms rather than them pushing their existing portfolio companies to become less innovative.[3] These deal selection results are also consistent with our findings that changes in venture-backed innovation occur fairly rapidly with the onset of recessions, as deal selection can likely change more quickly than the nature of existing startups.

Prior work suggests at least two reasons that venture investors may change their investment focus during downturns towards startups that enable them to conserve capital. First, limited partners, who are the ultimate source of capital for venture funds, typically reduce their alternative asset allocations during recessions as public market asset values decline, which can make the raising of follow-on funds more difficult. Townsend (2015) shows that venture capitalists with heavy exposure to information technology after the dot com collapse of the early 2000s were more likely to terminate funding for non-IT companies (e.g., biotechnology), suggesting that their inability to raise capital after the bust led to the failure of companies with positive net present values. Second, venture investors face pressure to provide additional capital to their existing portfolio companies during recessions, as other funding sources and exit opportunities for these firms are diminished in the near-term.

Facing a need to conserve capital to fund existing portfolio companies and uncertainty about raising new funds from limited partners due to the unpredictable

[3] These results are also consistent with survey evidence suggesting that venture capitalists view deal selection as being more important to their role than post-investment monitoring activities (Gompers et al. 2020).

length and severity of recessions, even venture groups that have abundant capital may anticipate future liquidity constraints and act accordingly. This mechanism is similar to the rollover risk problem identified in the corporate debt literature, where a firm's cost of debt reflects not only its own credit risk but also a liquidity premium due to illiquidity of the secondary debt market (Acharya, Gale, and Yorulmazer 2011; He and Xiong 2012; Brunnermeier and Oehmke 2013). In the VC context, Nanda and Rhodes-Kropf (2017) show theoretically that a forecast of limited future funding from other venture firms can lead otherwise healthy startups to not receive an initial round of financing, even if the VC firm itself is not constrained. In their model, innovative firms are most exposed to this risk.[4]

These sources of capital constraints—fundraising uncertainty and pressure to support existing portfolio companies—can lead venture funds to preserve cash and shift the focus of their early-stage investments toward less risky or novel startups that are closer to achieving cash flow break-even within a short period of time.[5] Late-stage firms are more likely to be cash-flow positive and should also benefit from venture capitalists' strategy of shoring up existing portfolio companies in downturns, implying that they should be less affected during recessions. Consistent with these predictions, we show that early-stage VC deal activity declines on average by about 30% during recessions, while late-stage activity is relatively unaffected. (To our knowledge, this is a new fact in the literature, alongside our novel innovation findings.) If changing technological opportunities were the primary mechanism for declining early-stage VC investment, we might expect to see variation across industries that is related to sensitivity to the business cycle. However, we find that the decline in VC investment during recessions exhibits surprisingly little

[4] In the companion paper to Nanda and Rhodes-Kropf (2017) (and the closest work to our paper), Nanda and Rhodes-Kropf (2013) shows that firms receiving their first venture financing in more active markets are more likely to go bankrupt, but conditional on going public, are valued more highly and have more patents. However, their focus on VC investment in boom times and importantly, do not consider innovation by VC-backed startups relative to innovation in the broader economy.

[5] See, for example, https://www.sequoiacap.com/article/rip-good-times

variation across industries.

We offer the first systematic analysis of the cyclicality of VC-backed innovation. Contrary to a common narrative in which VC-backed startups are relatively insulated from downturns, we document that deal activity is in fact highly pro-cyclical and that the relative quality of innovation declines more for VC-backed firms than for other types of firms during downturns. This is important because VC-backed startups play a disproportionately large role in economy-wide innovation, long-term job creation, and value formation. Our results imply that VC-backed firms, particularly those receiving their first early-stage investment, often do not have the luxury of shifting their innovation investments or types of innovation across the business cycle. Furthermore, we offer evidence that the shift away from high-quality innovation among early-stage VC-backed startups during recessions reflects changes in the types of firms that VC funds are willing to finance. The most plausible explanation for our findings is a perceived need to conserve capital during recessions, both to finance existing portfolio companies which may struggle and because the fundraising environment may become more challenging. In sum, the nature of financing in the VC industry means that it pushes overall innovation in the economy to be relatively more pro-cyclical.

Overall, our paper helps to shed light on the nature of innovation in downturns, which has long been puzzling to researchers. As noted above, these findings are consistent with many studies documenting the pro-cylicality of innovation in public firms and households, though the mechanisms may be quite different. For instance, Barlevy (2007) and Fabrizio and Tsolmon (2014) suggest that reduced ability during downturns to profit from commercializing ideas before competitors copy the insights may deter innovation; similarly, Comin and Gertler (2006) suggests profits from innovations may be greater during booms. Brown, Fazzari, and Petersen (2009) suggests that recently public firms may depend on cash flow and stock offerings to fund R&D, both of which are procyclical. Studying individual inventors, Bernstein, McQuade, and

Townsend (2021) find that household financial distress deters risky innovation, and Babina, Bernstein, and Mezzanotti (forthcoming) find that independent invention declined during the Great Depression. Related to the mechanism of capital supply, Moreira and Granja (2023) argue that financing constraints lead consumer goods firms to introduce fewer novel products during recessions.[6]

2 Data

To identify VC-backed firms and analyze how VC-backed innovation responded to past recessions, we combine the data from the Refinitiv VentureXpert database over the period 1976 to 2019 with patent data from the U.S. Patent and Trademark Office (USPTO). VentureXpert, along with Dow Jones' VentureSource (formerly VentureOne), are the two primary venture capital databases. We use VentureXpert because it starts earlier (1962 vs. 1994) and has been found to be more comprehensive in terms of investment coverage, which is important for our purposes.[7] VentureXpert records detailed information about the dates of venture financing rounds, the VC firms and startups involved, the amounts invested by each party, and the ultimate startup outcome, which allows us to understand how VC deal activity responded to past recessions.

VentureXpert is merged with patent data from the U.S. Patent and Trademark Office (USPTO) following the procedure outlined in Bernstein, Giroud, and Townsend (2016). Due to the time lag associated with granting of patents, we restrict the patent analyses to U.S. utility patents issued between January 1, 1976 and December 31, 2017. We examine

[6]This paper also contributes to the literature on cyclicality in venture capital and private equity, including Gompers and Lerner (2000), Kaplan and Schoar (2005), Axelson et al. (2013), Nanda and Rhodes-Kropf (2013), and Robinson and Sensoy (2016) and on the relationship between venture investors and their portfolio companies, including the important role of financial constraints (Kaplan and Strömberg 2003, 2004; Howell 2017, 2020; Ewens, Gorbenko, and Korteweg 2022).

[7]Maats et al. (2011) and Kaplan, Strömberg, and Sensoy (2002) compare VentureXpert against samples of financing rounds obtained from original sources and find reasonably good coverage, albeit with concerns about valuation and outcome data (the former of which is not used here).

citations to these patents through the end of 2019. Because we are studying the effects of U.S. recessions, we also further restrict the analysis to patents assigned to U.S. firms. The merged dataset consists of 2.68 million domestic utility patents. For each patent, we can observe the date it was applied for, the firm it was assigned to, its primary four-digit CPC field classification, the backward citations it made to other patents, and the forward citations other patents made to it.

We define recessions as the months from the peak to the trough identified in NBER business cycle data (https://www.nber.org/cycles.html). We proxy for innovation dates with patent application dates throughout our analysis. Thus, we consider an innovation to have originated during a recession if a patent based on that innovation was applied for during a recession. (The results are very similar if we move recession start and end dates forward two or three months, in case the market does not "know" it is in a recession at the beginning.) While there may be some lag time between when an innovation is discovered and a patent is applied for, it would not be in a firm's interest to delay. Hall, Griliches, and Hausman (1986) also provide evidence that such lags are not typically very long. In particular, they find that there is a strong relationship between contemporaneous R&D expenditures and patent applications, but a much weaker relationship between lagged R&D expenditures and patent applications. Perhaps more importantly, even if do we measure innovation timing with error, this would not bias us toward finding differential pro-cyclicality for VC-backed relative to non-VC-backed innovation.

2.1 Key Dependent Variables

We next outline the key variables used in our analysis:

VC-backed patent. We wish to examine innovation among firms that are in the portfolios of venture capitalists, not those that were financed by venture groups many years (or even decades) beforehand. Therefore we define a patent to be VC-backed if the firm it was assigned to was financed by a VC and its application date was between the assignee's first and last venture round dates. Of course, some patenting firms may continue to have active involvement of a VC in the years after its last venture round. In unreported analyses, we find that the results are robust to an alternative definition, which considers a patent to be affiliated with a VC if its application date is in the first four years after its assignee's first VC financing round. This period corresponds to the average period that a firm remains in a venture-capitalist's portfolio (Metrick and Yasuda 2010).

Top-cited patent. We characterize patents based on several measures from the innovation literature. The first measure is the number of forward (subsequent) citations a patent received from other patents granted through the end of 2019.[8] Forward citations are widely viewed as a good proxy for the quality of a patent and indicative of its knowledge spillovers. We define a top-cited patent to be one that is in the top 1% among all patents applied for in the same month.

Top originality score patent. Patent originality is a measure of how dispersed a patent's backward citations are across different fields, where fields are based on patents' primary four-digit CPC classifications. Thus, a patent is considered more original if it combines knowledge from many different areas. This measure is defined as one minus the sum of the squared ratio of (a) the number of backward citations going to patents with a primary assignment in each patent class and (b) the total number of such citations. We define a top originality score patent to be one that is in the top 1% among all patents applied for in the same month.

Top generality score patent. Patent generality is a measure of how dispersed a patent's forward citations are across different fields. A patent is considered more general if it influences subsequent innovations in many different areas. This measure is defined

[8] Although the patent data only run through the end of 2017, we extend the citation data through the end of 2019

analogously to originality. We define a top generality score patent to be one that is in the top 1% among all patents applied for in the same month.

Top "closeness to science" patent. We consider a patent to be closer to fundamental science the more that it cites academic publications. We define a top "closeness to science" patent to be one that is in the top 1% in terms of citations to academic research, among all patents applied for in the same month. The data on citations to academic citations comes from Marx and Fuegi (2020).

Top "closeness to quality science" patent. We consider a patent to be closer to high-quality fundamental science the more that it cites academic publications from journals whose impact factor is in the top quartile. The impact factor is calculated for year t as the number of times articles from years $t-1$ and $t-2$ were cited by other articles during year t, divided by the number of articles published during years $t-1$ and $t-2$. We define a top "closeness to quality science" patent to be one that is in the top 1% in terms of citations to high quality academic research, among all patents applied for in the same month.

3 Analysis of VC, Recessions, and Innovation

3.1 Procyclicality of Innovation

We begin by documenting the overall procyclicality of innovation, before turning to our main focus on the relative innovativeness of VC-backed firms. In doing so, we confirm and extend existing research. Some studies have focused on the cyclicality of R&D expenditure, such as Barlevy (2007) and Ouyang (2011), while others have tested specific cross-sectional predictions that emerge from procyclicality, such as industry variation (Fabrizio and Tsolmon 2014; Moreira and Granja 2023). Much of the literature on procyclicality relies on the Carnegie Mellon Survey or mid-twentieth century data and thus does not extend past the early 2000s.[9] The literature is also focused almost exclusively on publicly traded firms.[10] Therefore, it is an open question whether procyclicality has persisted through the 2010s.

To fill in this gap, Figure 1 shows the relationship between the stock market and patent production between 1945 and 2020. The top panel contains two raw time series: utility patents granted to U.S. inventors alongside the real S&P 500 Index, in 2023 prices.[11] The correlation is 0.91, which mostly reflects the rapid increase in both series post-1980. In the bottom panel, we normalize patents by the U.S. population and replace the level of the S&P with the Shiller cyclically adjusted P/E ratio (CAPE).[12] The correlation here is 0.62. It is clear that innovation is by no means countercyclical, as the Schumpeterian theory would predict. Conversely, there is a tight positive relationship between long-horizon innovative activity and the business cycle as measured by the stock market, a relationship that has persisted to the present day. This fact sets the stage for exploring whether VC dampens or contributes to the procyclicality of innovation.

3.2 The Relative Innovativeness of VC-Backed Firms

We first characterize the relative innovativeness of venture-backed firms by comparing their patents to the patents of other assignees. Table 1 presents, for domestic U.S. patent awards made between 1976 and 2017, the share of all patents and VC-backed patents that fell into each category defined in Section 2.1.

Venture-backed patents are more frequent in each of the areas of importance than the

[9] For example, Geroski and Walters (1995) examine major inventions in the UK between 1948 and 1983.

[10] There is also work on individual inventors, which has not examined long term dynamics (Bernstein, McQuade, and Townsend 2021; Babina, Bernstein, and Mezzanotti forthcoming).

[11] We gather long-horizon patent data from here. To account for the fact that there is typically a roughly two-year lag between when a patent is applied for and when it is ultimately granted, the patent time series in both graphs are shifted back by two years.

[12] The CAPE is a version of the price-to-earnings ratio that values a stock price relative to its earnings per share. The Shiller adjustment is to divide the price by the 10-year average inflation adjusted earnings to smooth fluctuations in corporate profits.

non-venture-backed ones. For instance, while 1% of all patents were unsurprisingly in the top 1% of most-cited patents, 2.9% of the venture-backed firms were.[13] Put another way, VC-backed patents were 2.9 times over-represented among these top-cited patents. The ratio is similar using other metrics, such as the top 1% in generality, originality, and academic citations. To ensure this is not an anomaly of the top 1%, the second half of the table finds similar over-representation in the top 10% of patents. For example, 22% of VC-backed patents are in the top 10% of most-cited patents.

3.3 The Temporal Pattern of Innovativeness

Next, we examine how these patterns change over time. In particular, we seek to understand how the relatively greater innovativeness of VC-backed firms varies over the business cycle. Figure 2 takes a first look at the data, plotting the share of patents assigned to venture capitalists that are in the top 1% of citations (relative to all patents awarded that month) less the VC share of all patents. The figure does not control for the changing technology mixture, nature of the patent assignees, or level of venture financing, but suggests that a number of recessions saw declines in the share of high-impact patents awarded to VC-backed firms.

We then turn to examining these patterns in a regression framework, where each observation is a single patent. We begin in Table 2 by estimating equations of the form:

$$\mathbb{1}(VC\text{-}Backed_{ict}) = \beta_1 \mathbb{1}(Recession_t) + \beta_2 log(VC\ Investment_t) + \gamma_c + \epsilon_{ict}, \qquad (1)$$

where i indexes patents, c indexes patent classes, and t indexes application months. The key variable of interest $1(Recession_t)$ is an indicator equal to one if the month the patent was applied for was during a recession (recall this is defined as being in a month from the

[13]In some cases, a share may be greater or less than 1%, due to the bunching in the distribution of citations and other metrics.

peak to the trough as identified by the NBER). $1(VCBacked_{ict})$ is an indicator equal to one if patent i is VC-backed, $log(VC\ Investment_t)$ is the log of aggregate VC investment during month t, and γ_c represent four-digit CPC patent class fixed effects. We use OLS models here and for subsequent binary outcomes because many of the groups defined by fixed effects – such as patent classes – have no successes (e.g. no VC-backed firms). Non-linear models such as logit drop the groups without successes. Angrist (2001) notes that OLS regressions do as well as logit ones in estimating marginal effects and often better with binary treatment variables. In settings with many fixed effects, Beck (2011) finds that OLS is superior. Standard errors are clustered by month.

The tables tell a consistent story. The estimates in Table 2 show that the share of patents associated with venture-backed firms falls during recessions. Moreover, this remains true after controlling for the reduced VC investment activity associated with recessionary periods. Specifically, the estimate in column 3 indicates that during recessions there is a 5.6% fall in the share of patents that are VC-backed (note the mean, 0.036, is shown in Table 1).

The production of high-impact patents follows a similar pattern. In Table 3, we estimate equations of the form:

$$Cites_{ict} = \beta_1 \mathbb{1}(VC\text{-}Backed_{ict}) \times \mathbb{1}(Recession_t) + \beta_2 \mathbb{1}(VC\text{-}Backed_{ict}) + \gamma_c + \gamma_t + \epsilon_{ict}, \quad (2)$$

where $Cites_{ict}$ is a measure of the citations received by patent i, γ_t represent month fixed effects, and all other variables are defined as in Equation 1.[14]

In columns 1–4, our measure of citations is an indicator equal to one if the patent was in the top percentile among patents with the same application month. Beginning with column 1, we estimate β_1 to be negative and statistically significant at the 10% level.

[14]The main effect of recessions is absorbed by the month fixed effects, but the interaction between recessions and VC-backed patents is identified.

This means that the probability of a VC-backed patent being in the top percentile is lower during recessions than during normal times. In column 2, we also estimate a more stringent specification, controlling for patent class by month fixed effects. In this case, we are comparing patents from the same four-digit CPC patent class, which were applied for in the same month. With this more stringent specification, the result is similar, but significant at the 5% level.

To interpret the magnitudes, we first note that we estimate β_2 to be strongly positive and statistically significant. This means that during normal times, VC-backed patents are significantly more likely to be top cited among their cohort. For example, in column 2 the estimates suggest that VC-backed patents are 1.5 percentage points more likely to be top cited than the average non-VC-backed patent. By construction, the baseline probability is 1%. In other words, VC-backed patents are 2.5 times more likely to be top-cited patents during normal times. However, during recessions, VC-backed patents are only 1 percentage point, or 2x, more likely to be top cited.

In columns 3–4, we partition the VC-backed indicator into two variables: an indicator for whether the patent was assigned to an early-stage VC-backed firm; and an indicator for whether the patent was assigned to a late-stage VC-backed firm. As elsewhere in the paper, the stage of the firm is based on VentureXpert's categorization of its most recent financing round preceding the patent application date. We find that the decline in citations for VC-backed firms during recessions is strongly concentrated among those still at an early stage of development. Column 3 indicates that early-stage VC-backed patents are 2 percentage points more likely to be top cited than the average non-VC-backed patent, but this falls to just 1 percentage point in recessions. Indeed, we find no decline in citations during recessions for VC-backed firms at a later stage of development.

Finally, in columns 5–8, rather than examining whether a patent is top cited among its cohort, we change the dependent variable to the log of the number of citations the patent received. With this dependent variable, we again find that there is a decline among

VC-backed early-stage firms during recessions and no decline among VC-backed late-stage firms. This means that not only are patents of VC-backed early-stage firms less likely to be in the right tail of the citation distribution during recessions, but they are less cited on average as well. For most of our analysis, we focus on the right tail, however, because that is where the most consequential patents are located. To illustrate, an increase in mean citations could be entirely driven by changes in the left tail of the distribution, but this would be less economically important.

We demonstrate that our results are robust to different definitions of the right tail in Appendix Table A.1. First, we find similar results when we define cohorts based on application year rather than month. Second, we find similar results when we examine the top 10% within a cohort as opposed to the top 1%. In unreported analysis, we find very similar results to the main estimates when we move forward the recession dates by two or three months, indicating that the results are not sensitive to when precisely the beginning of the recession is specified.

In Table 4, we repeat the analysis of Table 3 using patent originality and generality as the dependent variables. As defined in Section 2.2, patent originality is a measure of the breadth of the technology fields on which a patent relies. In columns 1–4, we find that patent originality significantly declines during recessions among VC-backed firms. In particular, the estimates in column 2 suggest that VC-backed patents are 2.2 times more likely to be in the right tail of the originality distribution during normal times but only 1.7 times more likely during recessions. As with citations, we also find that the decline in patent originality is concentrated among early-stage VC-backed firms. In fact, there is no decline in patent originality among late-stage VC-backed firms. In columns 5–8, we explore patent generality, which is a measure of the breadth of the technology fields that a patent subsequently influences. We find that there is no significant decline in patent generality for the average VC-backed firm during a recession. However, there is a significant decline for early-stage VC-backed firms. Overall the results of Table 4 suggest that not only do early-stage VC-backed patents become less cited during recessions, they also draw upon and influence innovations in narrower fields.

In Table 5, we consider how closeness to fundamental science changes for VC-backed patents over the business cycles. As described in Section 2.2, we define closeness to science based on the number of citations a patent makes to academic publications. In columns 1–4, we find that closeness to science also significantly declines during recessions for VC-backed firms. This time, the estimates in column 2 suggest that VC-backed patents are two times more likely to be in the right tail of the closeness to science distribution during normal times but only 1.6 times more likely during recessions. Once again, we also find that the decline in closeness to science is concentrated among early-stage VC-backed firms and that there is no decline in closeness to science among late-stage VC-backed firms. In columns 5–8, we find qualitatively similar results—although statistically weaker—when we define closeness to science based on citations to only top-quartile academic publications in terms of impact factor. Overall, the results of Table 5 suggest that early-stage VC-backed patents also become less close to fundamental science during recessions.

One interesting question is whether the declines in the quality of innovation documented above are driven by changes across firms or within them. In other words, are the new early-stage firms that venture investors finance during recessions less innovative, or do existing early-stage firms become less innovative during recessions? To shed light on this question, we repeat the analysis of Table 3, now including patent assignee (i.e., firm) fixed effects in all specifications. The results, in Table 6, reveal no evidence of within-firm declines during recessions. What this tells us is that conditional on patenting both during a boom and during a recession, firms do not change the innovativeness of their patenting behavior. This means that the results could either stem from venture capitalists investing in new firms that are less innovative in recessions, or from firms that patent for the first time during recessions being less innovative, regardless of when they were most recently funded.

The results in Table 6 are consistent with survey evidence suggesting that venture investors view deal selection as being more important to their role than post-investment monitoring activities (Gompers et al. 2020). These results are also consistent with our findings that changes in venture-backed innovation occur fairly rapidly with the onset of recessions, as deal selection can likely change more quickly than the nature of existing startups.

3.4 Venture Capital Investment in Recessions

Interestingly and consistent with the innovation results, Table 7 shows that at the monthly level, early-stage VC activity falls in recessions, while late-stage activity does not.[15] While the cyclicality of VC investment has been documented in prior work, we believe that the particular sensitivity of *early-stage* investment is new to the literature.

The dependent variables in Table 7 are the total number of deals (columns 1-4) and the log dollar amount of deals (columns 5-8). In each case, we consider in the first column all deals, in the second column only early-stage deals, in the third column only late-stage deals, and in the fourth column the difference between early- and late-stage deals. Our primary outcome of interest is number of deals, since this represents new firms funded and is most relevant for understanding entry of innovative, VC-backed startups. We find robust declines in the number of early deals, which fall in recessions by 30% (column 2). Like the innovation results, the relationship is quite similar if we move forward recession dates by two or three months (not reported).

Meanwhile, there is no measurable relationship between recessions and late-stage activity. The coefficient is negative but small and statistically insignificant (column 3). The difference between the number of early and late deals is statistically significant

[15]Early Stage and Late Stage are defined by VentureXpert and correspond to the development stage of the startup rather than a particular round of financing. Figure 3 plots the number of venture deals, the S&P 500 index, and NBER recessions.

(column 4). This pattern also holds more weakly for the dollar volume of deals. For example, the amount of early-stage investment falls by 39% (column 6). In this case, there is a large negative coefficient for late stage (column 7), but it is not significantly different from zero, and there is no significant difference between early and late stage (column 8).[16] In sum, there is a consistent decline in early-stage VC deals during recessions.

3.5 Investment Opportunities vs. Capital Supply

What can explain this decline in the quantity and quality of innovative output among newly patenting, VC-backed firms during recessions? We are interested in whether the effect primarily reflects a change in investment opportunities, or whether it reflects a change in the way capital is deployed by venture capitalists; that is, a change in the selection of deals by venture capitalists. Several analyses point to shifts in capital supply playing an important role. Our intention is not to rule out the presence of other factors that could contribute to the observed patterns of innovation, but instead to present evidence that shifts in capital supply are, to perhaps a surprising extent, important for explaining the results.

Our first analysis is based on the timing of a startup's fundraising. Suppose that the mechanism is demand for goods or a change in new technological opportunities during recessions. Then conditional on a VC-backed startup producing a patent in a recession, it should be lower quality regardless of when that startup was last financed. On the other hand, suppose instead the mechanism is that the supply of VC financing is lower and perhaps less oriented towards risky inventions during recessions. Then we expect that those startups with the lucky timing to have raised capital somewhat before the

[16] One question is whether these results reflect only a particular recession or period. In Appendix Table A.3, we omit each recession in turn in Panel A, focusing on the number of deals (i.e., repeating column 2 from Table 7) The results do not reflect any particular period or recession.

recession, which have a relatively plentiful cash "runway," will be more insulated from the negative effects of recessions on patent quality. That is, in a capital supply channel, differences across firms in innovation during recessions could stem not only from their extensive margin ability to raise initial VC, but also from characteristics of their most recent round. VC investment that does occur during recessions might come with less tolerance for risky, capital-intensive experimentation.

We find that timing of fundraising matters greatly to our findings. In Table 8, we divide early-stage VC-backed patents into two categories based on fundraising timing and interact them with whether the patent was applied for during a recession, as above. The first category, represented with the binary variable "Raised Outside Boom," indicates that the most recent round occurred either during the recession or prior to six months before the first month of the recession. The second category, represented with the binary variable "Raised During Boom," indicates that the most recent round occurred in the six months before the beginning of the recession. These startups likely had more runway before needing to raise another round of financing, implying they are less likely to face constraints from the supply of capital.

We show the results for both the dependent variables of being in the top 1% of citations (Table 8 columns 1-2) and log number of citations (Table 8 columns 3-4). The estimates in all four columns show that our main findings are driven by startups that raised outside the boom period. Startups that raised during the market peak produce on average more highly cited patents, though this is not significant (columns 1-2) and do not produce more or less top-cited patents (columns 3-4). (Note that industry is controlled for with patent class or patent class by month fixed effects.) In sum, this cross-sectional exercise supports the capital supply channel because it demonstrates that the timing of recent fundraising matters for determining what type of innovation firms do in recessions.

Our second analysis is based on the fact that limited partners, who are the ultimate source of capital for venture funds, typically reduce their alternative asset allocations during recessions¿ Venture investors consequentially often face pressure to provide additional capital to their existing portfolio companies during recessions, as other funding sources and exit opportunities for these firms are diminished in the near term. Similar to the rollover risk problem identified in the corporate debt literature, where a firm's cost of debt reflects not only its own credit risk but also a liquidity premium due to illiquidity of the secondary debt market (Acharya, Gale, and Yorulmazer 2011; He and Xiong 2012; Brunnermeier and Oehmke 2013), a forecast of limited future funding from other venture firms can lead to a drop in venture capital funding to new firms, even if the VC firm itself is not constrained. In the VC context, Nanda and Rhodes-Kropf (2017) show theoretically that innovative firms may be most exposed to this risk, leading venture investors to shift their investments in such times to less innovative startups.

To explore this version of the capital supply channel, in Table 9 we examine "follow-on" deals, which we define as deals in which the lead investor participated in a previous round of financing for the company. That is, we identify deals in which the lead investor previously invested in the company being financed. We construct the dependent variable as the follow-on share of all deals or deal amount. For example, column 1 shows the share of the total number of VC deals that are follow-on deals, while column 2 shows the share of the total number of early-stage VC deals that are follow-on deals. Note that a company can have multiple early rounds; indeed, the average VC-backed startup with any early deals has 1.7 early deals.

Comparing the estimates in Table 9 to those in Table 7 indicates that the decline in early-stage VC during recessions is driven entirely by investments in companies that are new from the perspective of the VC firm. Columns 2 and 5 show that there is no relationship between recessions and early-stage follow-on deals, implying that the results in Table 7 columns 2 and 6 are driven by investments in companies that are not already in the VC firm's portfolio. In contrast, there is a strong positive relationship between recessions and overall follow-on deals, both in terms of number of deals (column 1) and amount of deals (column 4). Specifically, the share of deals that are follow-on increases by 3.4 percentage points in recessions, which is 15% of the mean.

This result indicates a shift in the composition of VC activity during recessions towards existing portfolio companies. This shift is particularly salient for the amount of late-stage VC investment (columns 3 and 6). While there is a negative but insignificant relationship between recessions and amount of late-stage VC (Table 7 column 5), during recessions the share of late-stage VC amounts composed of follow-on deals increases by 5.8 percentage points, more than 17% of the mean (Table 9 column 6). This suggests that companies whose initial investors lack the dry powder to do follow-on deals may find themselves especially vulnerable in a recession and shift their financing to less risky and less innovative startups.

In addition to more funding from existing investors, startups may require more advice or monitoring during recessions. As GPs have limited time, the need to spend more time with existing portfolio companies that are struggling with both the demand and financing implications of a recession may come at the expense of sourcing new deals. For example, a GP at Battery Ventures urges CEOs in "tough economic periods" to "over-communicate when it comes to informing your board about [problems] and exploring solutions."[17]

While likely important in certain instances, the role of technological or market opportunities does not appear as salient in systematically explaining the pattern of results we document. First, we do not observe declines in investment activity and high-impact innovation among late-stage rounds, where one may have expected to see a greater decline if changing demand was a driver for the decline in VC financing and innovation. In addition, we examine the industry composition of VC deals across historical recessions. If a demand channel explains the decline in VC activity, we would expect to see relatively larger declines during recessions in sectors such as consumer goods than in sectors such as biotechnology, where demand for products is long term

[17] https://www.battery.com/powered/communicate-with-board-during-tough-times/

and less sensitive to business cycles. In Appendix Table A.2, we estimate how recessions affect the industry shares of VC deals. We use VentureXpert's major industry categories. For six of the eight sectors, there is no relationship; all the coefficients are near-zero and insignificant. For example, there is no increase in the biotech share of VC deals during recessions (column 1), and no decrease in the consumer goods share (column 6). We do observe a positive, significant correlation for the industrial and other categories.

4 Conclusion

The cyclical nature of innovation, particularly its behavior during downturns, has long been puzzling to researchers. We explore these issues here in the context of venture capital, an increasingly important intermediary in the promotion of innovation. This paper shows that while patents filed by VC-backed firms are of significantly higher quality than the average patent, VC-backed innovation is substantially more procyclical. We trace this to changes in innovation by early-stage VC-backed startups. We present evidence that one channel may be frictions in capital supply shifting the type of early-stage firms that venture capitalists back during downturns. While this is likely not the only channel at play, it is an important and surprising mechanism.

There are a variety of open questions about the implications of these patterns for social and private optimality. It is possible that the decline in high-impact VC-driven innovation during recessions is socially detrimental, especially given the over-representation of VC-backed assignee firms among the most influential patents. The private optimality of the pro-cyclical patterns is more complex. Whatever the social consequences, it may well be privately optimal for venture investors to cut back on financing ground-breaking work in periods when risk is high and liquidity is restricted, particularly if this work will take longer to reach the marketplace. These issues deserve careful scrutiny. More generally, our work points to untangling potential explanations for the extreme pro-cyclicality of early-stage VC investments as an important area of future inquiry.

References

Acemoglu, Daron, Ufuk Akcigit, Harun Alp, Nicholas Bloom, and William Kerr. 2018. "Innovation, reallocation, and growth." *American Economic Review* 108 (11):3450–3491.

Acharya, Viral V., Douglas Gale, and Tanju Yorulmazer. 2011. "Rollover risk and market freezes." *Journal of Finance* 66 (4):1177–1209.

Aghion, Philippe, Philippe Askenazy, Nicolas Berman, Gilbert Cette, and Laurent Eymard. 2012. "Credit constraints and the cyclicality of R&D investment: Evidence from France." *Journal of the European Economic Association* 10 (5):1001–1024.

Aghion, Philippe and Gilles Saint-Paul. 1998. "Virtues of bad times interaction between productivity growth and economic fluctuations." *Macroeconomic Dynamics* 2 (3):322–344.

Akcigit, Ufuk, Sina T. Ates, Josh Lerner, Richard R. Townsend, and Yulia Zhestkova. forthcoming. "Fencing off Silicon Valley: Cross-border venture capital and technology spillovers." *Journal of Monetary Economics* .

Angrist, Joshua D. 2001. "Estimation of limited dependent variable models with dummy endogenous regressors: simple strategies for empirical practice." *Journal of Business and Economic Statistics* 19 (1):2–28.

Arora, Ashish, Sharon Belenzon, and Lia Sheer. 2021. "Knowledge spillovers and corporate investment in scientific research." *American Economic Review* 111 (3):871–898.

Axelson, Ulf, Tim Jenkinson, Per Strömberg, and Michael S. Weisbach. 2013. "Borrow cheap, buy high? The determinants of leverage and pricing in buyouts." *Journal of Finance* 68 (6):2223–2267.

Babina, Tania, Asaf Bernstein, and Filippo Mezzanotti. forthcoming. "Financial disruptions and the organization of innovation: Evidence from the Great Depression." *Review of Financial Studies* .

Barlevy, Gadi. 2007. "On the cyclicality of research and development." *American Economic Review* 97 (4):1131–1164.

Beck, Nathaniel. 2011. "Is OLS with a binary dependent variable really OK? Estimating (mostly) TSCS models with binary dependent variables and fixed effects." Unpublished working paper, NYU.

Bernstein, Shai, Xavier Giroud, and Richard R Townsend. 2016. "The impact of venture capital monitoring." *Journal of Finance* 71 (4):1591–1622.

Bernstein, Shai, Josh Lerner, and Filippo Mezzanotti. 2019. "Private equity and financial fragility during the crisis." *Review of Financial Studies* 32 (4):1309–1373.

Bernstein, Shai, Timothy McQuade, and Richard R. Townsend. 2021. "Does household wealth shocks affect productivity? Evidence from innovative workers during the Great Recession." *Journal of Finance* 76 (1):57–111.

Bloom, Nicholas, Charles I. Jones, John Van Reenen, and Michael Webb. 2020. “Are ideas getting harder to find?” *American Economic Review* 110 (4):1104–44.

Brown, James R., Steven Fazzari, and Bruce C. Petersen. 2009. “Financing innovation and growth: Cash flow, external equity, and the 1990s R&D boom.” *Journal of Finance* 64 (1):151–185.

Brunnermeier, Markus K. and Martin Oehmke. 2013. “The maturity rat race.” *Journal of Finance* 68 (2):483–521.

Caballero, Ricardo J and Mohamad L Hammour. 1994. “The cleansing effect of recessions.” *American Economic Review* 84 (5):1350–1368.

Comin, Diego and Mark Gertler. 2006. “Medium-term business cycles.” *American Economic Review* 96 (3):523–551.

Cooper, Russell and John Haltiwanger. 1993. “The aggregate implications of machine replacement: Theory and evidence.” *American Economic Review* 83 (3):360–382.

Decker, Ryan, John Haltiwanger, Ron Jarmin, and Javier Miranda. 2014. “The role of entrepreneurship in US job creation and economic dynamism.” *Journal of Economic Perspectives* 28 (3):3–24.

Ewens, Michael, Alexander S Gorbenko, and Arthur Korteweg. 2022. “Venture capital contracts.” *Journal of Financial Economics* 143:131–158.

Fabrizio, Kira R. and Ulya Tsolmon. 2014. “An empirical examination of the procyclicality of R&D investment and innovation.” *Review of Economics and Statistics* 96 (4):662–675.

Geroski, Paul A and Chris F Walters. 1995. “Innovative activity over the business cycle.” *The Economic Journal* 105 (431):916–928.

Gompers, Paul and Josh Lerner. 2000. “Money chasing deals? The impact of fund inflows on private equity valuations.” *Journal of Financial Economics* 55 (2):281–325.

Gompers, Paul A, Will Gornall, Steven N Kaplan, and Ilya A Strebulaev. 2020. “How do venture capitalists make decisions?” *Journal of Financial Economics* 135 (1):169–190.

Gornall, Will and Ilya A. Strebulaev. 2015. “The economic impact of venture capital: Evidence from public companies.” Unpublished Working Paper.

Griliches, Zvi. 1984. “Patent statistics as economic indicators: A survey.” In *R&D and Productivity: The Econometric Evidence*, edited by Zvi Griliches. University of Chicago Press, 287–343.

Hall, Bronwyn H, Zvi Griliches, and Jerry A Hausman. 1986. “Patents and R&D: Is There a Lag?” *International Economic Review* 27 (2):265–283.

Hall, Robert E. 1991. “Recessions as reorganizations.” *NBER macroeconomics annual* 6:17–47.

He, Zhiguo and Wei Xiong. 2012. “Rollover risk and credit risk.” *Journal of Finance* 67 (2):391–430.

Howell, Sabrina T. 2017. “Financing innovation: Evidence from R&D grants.” *American Economic Review* 107 (4):1136–64.

———. 2020. “Reducing information frictions in venture capital: The role of new venture competitions.” *Journal of Financial Economics* 36 (3):676–694.

Kaplan, Steven N. and Antoinette Schoar. 2005. “Private equity performance: Returns, persistence, and capital flows.” *Journal of Finance* 60 (4):1791–1823.

Kaplan, Steven N. and Per Strömberg. 2003. “Financial contracting theory meets the real world: An empirical analysis of venture capital contracts.” *Review of Economic Studies* 70 (2):281–315.

———. 2004. “Characteristics, contracts, and actions: Evidence from venture capitalist analyses.” *Journal of Finance* 59 (5):2177–2210.

Kaplan, Steven N., Per Strömberg, and Berk A Sensoy. 2002. “How well do venture capital databases reflect actual investments?” Unpublished Working Paper.

Kortum, Samuel and Josh Lerner. 2000. “Assessing the contribution of venture capital to innovation.” *RAND Journal of Economics* 31 (4):674–692.

Lerner, Josh and Ramana Nanda. 2020. “Venture Capital's Role in Financing Innovation: What We Know and How Much We Still Need to Learn.” *Journal of Economic Perspectives* 34 (3):237–261.

Maats, Frederike, Andrew Metrick, Ayako Yasuda, Brian Hinkes, and Sofia Vershovski. 2011. “On the consistency and reliability of venture capital databases.” Unpublished Working Paper.

Marx, Matt and Aaron Fuegi. 2020. “Reliance on science: Worldwide front-page patent citations to scientific articles.” *Strategic Management Journal* 41 (9):1572–1594.

Metrick, Andrew and Ayako Yasuda. 2010. “The economics of private equity funds.” *Review of Financial Studies* 23 (6):2303–2341.

Moreira, Sara and Joao Granja. 2023. “Product innovation and credit market disruptions.” *Review of Financial Studies* 36 (5):1930–1969.

Nanda, Ramana and Matthew Rhodes-Kropf. 2013. “Investment cycles and startup innovation.” *Journal of Financial Economics* 110 (2):403–418.

———. 2017. “Financing risk and innovation.” *Management Science* 63 (4):901–918.

Ouyang, Min. 2011. “On the Cyclicality of R&D.” *Review of Economics and Statistics* 93 (2):542–553.

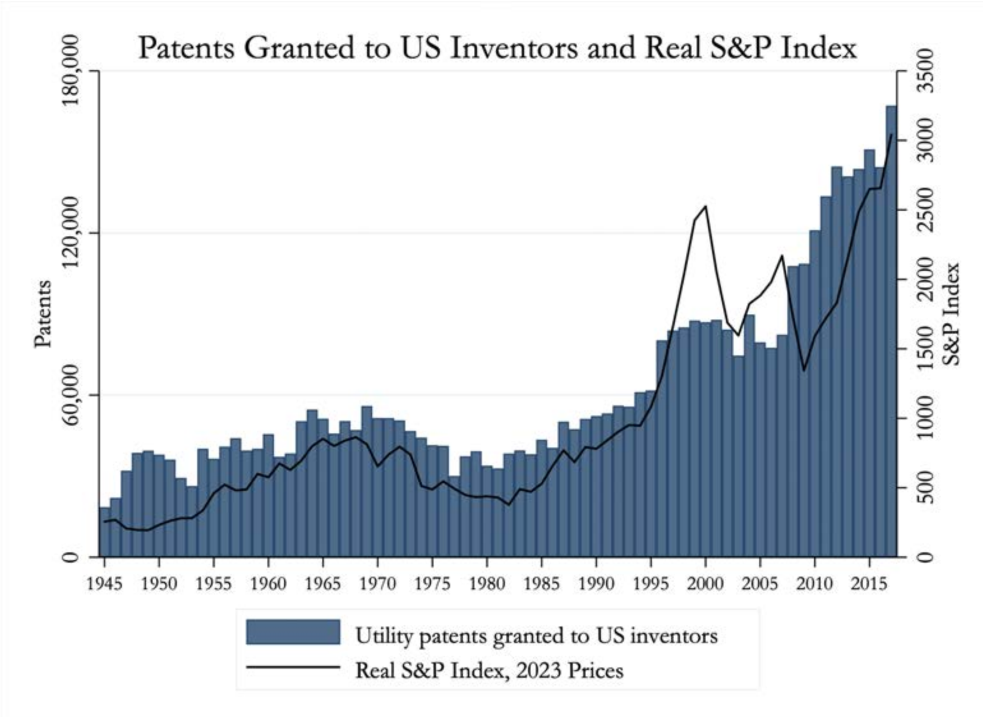
Puri, Manju and Rebecca Zarutskie. 2012. “On the life cycle dynamics of venture-capital-and non-venture-capital-financed firms.” *Journal of Finance* 67 (6):2247–2293.

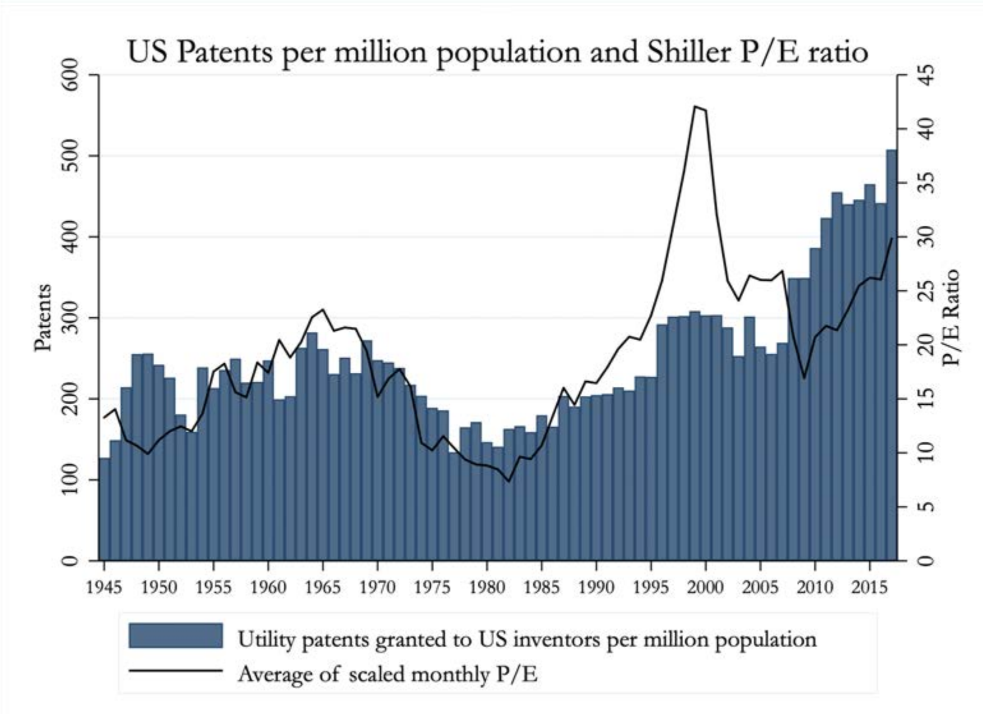
Robinson, David T. and Berk A. Sensoy. 2016. "Cyclicality, performance measurement, and cash flow liquidity in private equity." *Journal of Financial Economics* 122 (3):521–543.

Schumpeter, Joseph A. 1939. *Business Cycles*, vol. 1. New York: McGraw-Hill.

Townsend, Richard R. 2015. "Propagation of financial shocks: The case of venture capital." *Management Science* 61 (11):2782–2802.

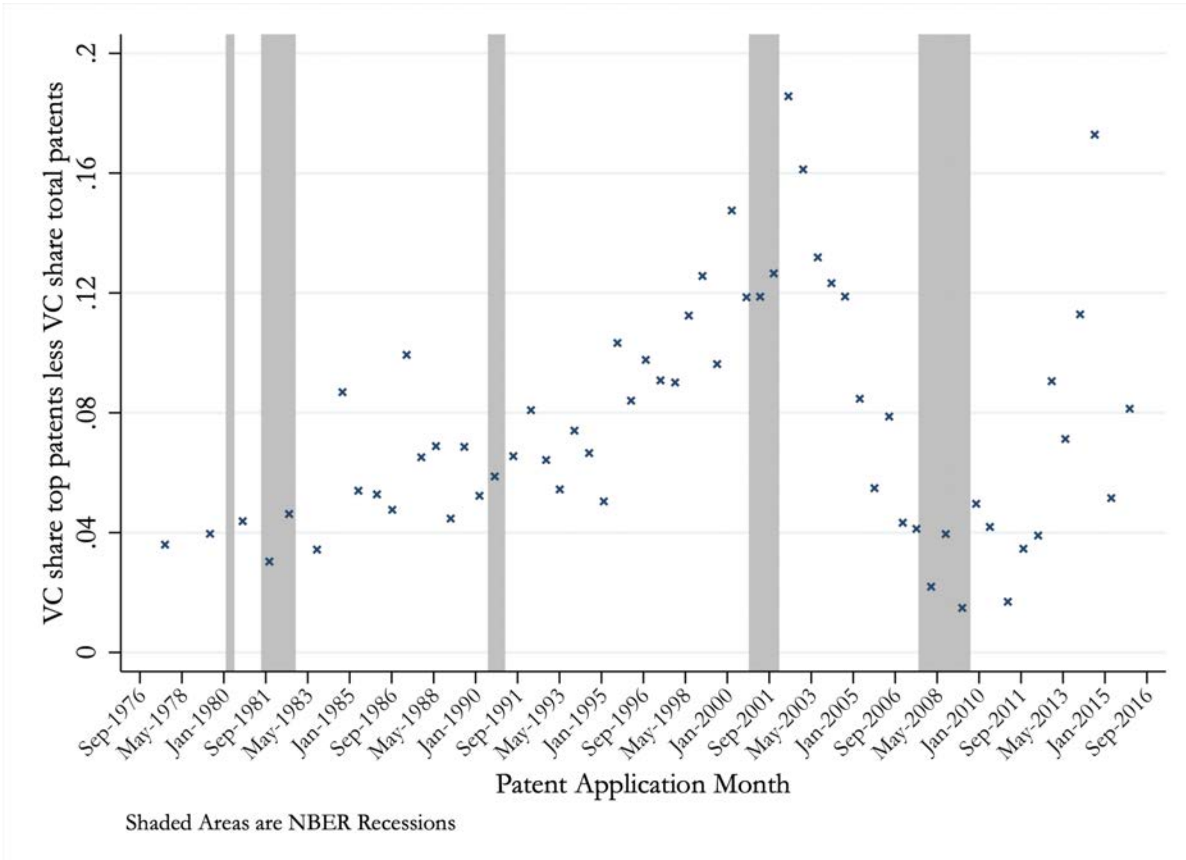
Figure 1: Patenting and Market Cycles





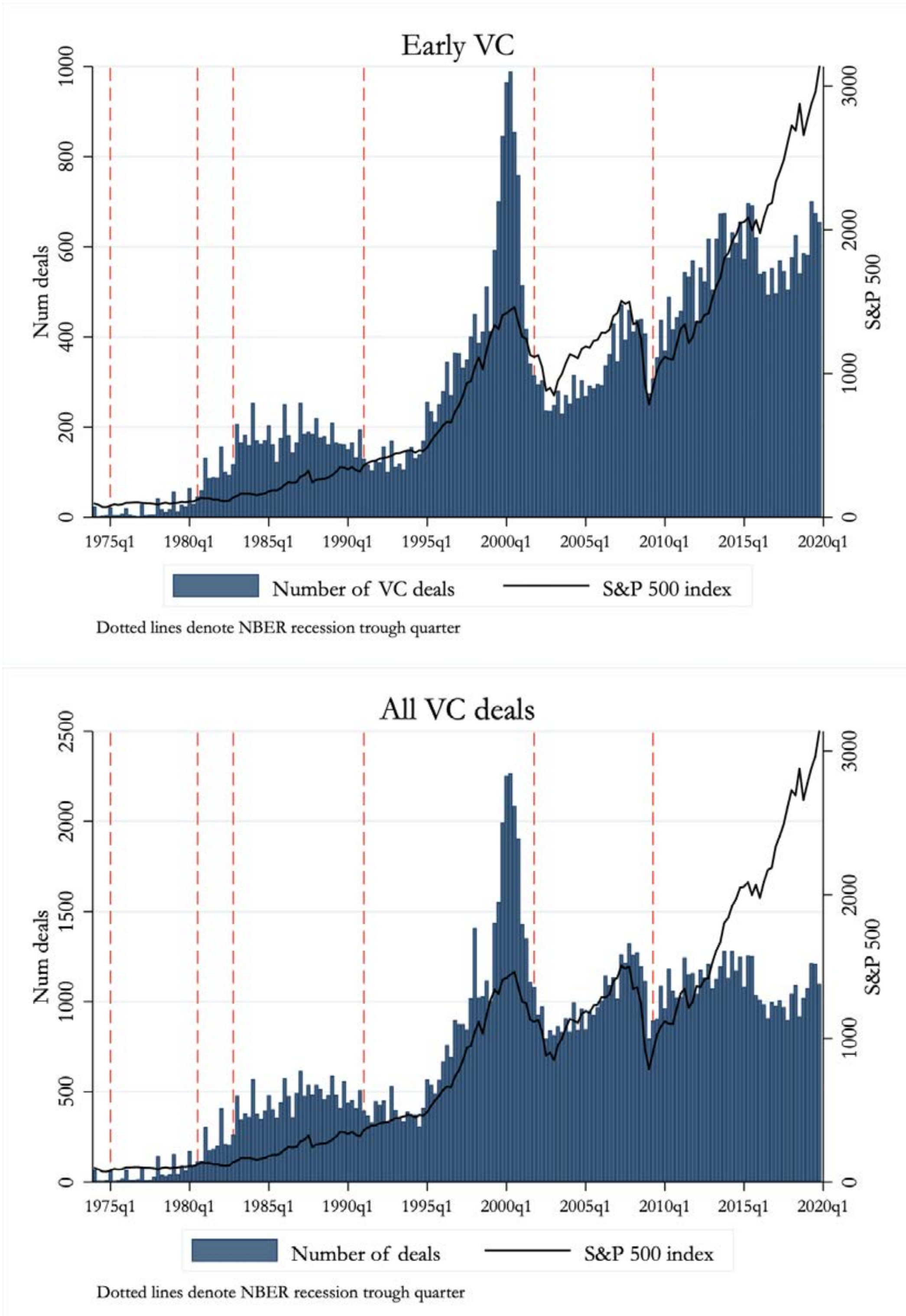
These figures show the relation between US patenting and the stock market. The top graph shows the time series for utility patents granted to US inventors alongside the real S&P 500 Index (2023 prices). The bottom graph normalizes patents by the US population and normalizes the level of the S&P using the Shiller cyclically adjusted P/E ratio (CAPE). Patents are shifted back by two years to account for the time between application and grant.

Figure 2: VC-backed Startup Share of Top Quality Patents Less VC share of Total Patents



This figure shows the difference between the share of VC patents that are in the top 1% of the citations (relative to all patents applied for in the same month) less the share of observations that are venture-backed. The data are presented as a binscatter with 80 equal-sized bins between January 1, 1976 and December 31, 2015 (subsequent data on citations exhibit strong truncation bias). Vertical shaded regions represent the peak-to-trough period defining NBER recessions. Sources: USPTO, VentureXpert.

Figure 3: VC Investment and Market Cycles



These figures show the quarterly number of VC deals. The top graph shows only early VC deals, while the bottom graph shows all VC deals. The red lines represent NBER recession trough quarters. The black line represents the stock market S&P 500 index. Source: VentureXpert.)

Table 1: Summary Statistics

This table presents summary statistics for the key variables. Observations are utility patents awarded between between January 1, 1976 and December 31, 2017 and assigned to a U.S. firm. *VC-Backed* is an indicator variable equal to one if one of the patent assignees is a VC-backed firm as of the patent application date. A patent assignee is defined as being VC-backed as of the patent application date if the patent application date is between the assignee's first VC financing round and its last VC financing round. *Top citations* is an indicator variable equal to one if the patent is in the top 10% or 1% of forward citations among patents from the same application month cohort. *Top originality* is an indicator variable equal to one if the patent is in the top 10% or 1% of originality among patents from the same application month cohort. *Top generality* is an indicator variable equal to one if the patent is in the top 10% or 1% of generality among patents from the same application month cohort. *Top closeness to science* is an indicator variable equal to one if the patent is in the top 10% or 1% of backward citations to academic research among patents from the same application month cohort. *Top closeness to quality science* is an indicator variable equal to one if the patent is in the top 10% or 1% of backward citations to academic research published in top journals among patents from the same application month cohort. Column 1 shows the proportion of patents that fall into each category. Column 2 shows the proportion of VC affiliated patents that fall into each category. Column 3 shows the ratio of column 2 to column 1.

	All Patents Mean	VC Patents Mean	Ratio
$\mathbb{1}$(VC-Backed)	0.036		
$\mathbb{1}$(Top 1% Citations)	0.010	0.029	2.90
$\mathbb{1}$(Top 1% Originality)	0.010	0.021	2.10
$\mathbb{1}$(Top 1% Generality)	0.010	0.029	2.90
$\mathbb{1}$(Top 1% Closeness to Sci.)	0.010	0.027	2.70
$\mathbb{1}$(Top 1% Closeness to Quality sci.)	0.010	0.026	2.60
$\mathbb{1}$(Top 10% Citations)	0.102	0.220	2.16
$\mathbb{1}$(Top 10% Originality)	0.100	0.189	1.89
$\mathbb{1}$(Top 10% Generality)	0.100	0.220	2.20
$\mathbb{1}$(Top 10% Closeness to Sci.)	0.107	0.209	1.95
$\mathbb{1}$(Top 10% Closeness to Quality sci.)	0.083	0.183	2.20
Observations	2,679,343	95,945	2,679,343

Table 2: Relationship Between Recessions and VC-Backed Patents

This table shows the OLS relationship between recessions and VC-backed patents. Observations are utility patents awarded between between January 1, 1976 and December 31, 2017 and assigned to a U.S. firm. *VC-Backed Patent* is an indicator variable equal to one if one of the patent assignees is a VC-backed firm as of the patent application date. A patent assignee is defined as being VC-backed as of the patent application date if the patent application date is between the assignee's first VC financing round and its last VC financing round. *Log VC investment* is the log of aggregate VC investment in U.S. startups during the month the patent was applied for. *Recession* is an indicator variable equal to one if the U.S. was in a recession during the month the patent was applied for according to the NBER Business Cycle Dating Committee. *Class FE* represent class fixed effects based on the patents primary, four-digit CPC class. Standard errors are clustered by application month. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	$\mathbb{1}$(VC-Backed Patent)		
	(1)	(2)	(3)
$\mathbb{1}$(Recession)	-0.003***		-0.002**
	(0.001)		(0.001)
Log VC Investment		0.004***	0.004***
		(0.000)	(0.000)
Patent Class FE	Yes	Yes	Yes
R^2	0.020	0.022	0.022
Observations	2,676,035	2,676,035	2,676,035

Table 3: Relationship Between Recessions and VC-backed Patent Citations

This table shows the OLS relationship between recessions and VC-backed patent citations. Observations are utility patents awarded between between January 1, 1976 and December 31, 2017 and assigned to a U.S. firm. The dependent variable in columns 1-4 is an indicator for the number of forward cites being in the top 1% among patents applied for in the same month. The dependent variable in columns 5-8 is the log of one plus the total number of forward citations to the patent. *VC-Backed* is an indicator variable equal to one if one of the patent assignees is a VC-backed firm as of the patent application date. A patent assignee is defined as being VC-backed as of the patent application date if the patent application date is between the assignee's first VC financing round and its last VC financing round. *Recession* is an indicator variable equal to one if the U.S. was in a recession during the month the patent was applied for according to the NBER Business Cycle Dating Committee. *Early Stage* is an indicator variable equal to one if the patent assignee was seed stage or early stage as of its most recent VC financing round according to VentureXpert. *late-stage* is an indicator variable equal to one if the patent assignee was not seed stage or early stage as of its most recent VC financing round. *Patent Class FE* represent class fixed effects based on the patent's primary four-digit CPC classification. *Month FE* represent month fixed effects. *Patent Class X Month FE* represent patent class by month fixed effects. Standard errors are clustered by application month. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Top 1% Cites (Within Month)				Log(1+Cites)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{1}$(Recession) × $\mathbb{1}$(VC-Backed)	-0.005*	-0.005**			-0.036	-0.019		
	(0.003)	(0.003)			(0.026)	(0.024)		
$\mathbb{1}$(VC-Backed)	0.014***	0.015***			0.374***	0.362***		
	(0.001)	(0.001)			(0.009)	(0.008)		
$\mathbb{1}$(Recession) × $\mathbb{1}$(VC-Backed and Early Stage)			-0.010***	-0.009***			-0.118***	-0.087***
			(0.003)	(0.003)			(0.028)	(0.025)
$\mathbb{1}$(VC-Backed and Early Stage)			0.020***	0.021***			0.472***	0.446***
			(0.002)	(0.002)			(0.014)	(0.014)
$\mathbb{1}$(Recession) × $\mathbb{1}$(VC-Backed and Late Stage)			-0.003	-0.004			-0.005	0.006
			(0.003)	(0.003)			(0.032)	(0.031)
$\mathbb{1}$(VC-Backed and Late Stage)			0.012***	0.013***			0.337***	0.330***
			(0.001)	(0.001)			(0.010)	(0.010)
Patent Class FE	Yes	No	Yes	No	Yes	No	Yes	No
Month FE	Yes	No	Yes	No	Yes	No	Yes	No
Patent Class × Month FE	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.027	0.082	0.027	0.082	0.275	0.349	0.275	0.349
Observations	2,241,808	2,241,808	2,241,808	2,241,808	2,241,808	2,241,808	2,241,808	2,241,808

Table 4: Relationship Between Recessions and VC-Backed Patent Originality and Generality

This table shows the OLS relationship between recessions and VC-backed patent originality/generality. Observations are utility patents awarded between between January 1, 1976 and December 31, 2017 and assigned to a U.S. firm. The dependent variable in columns 1-4 (5-8) is an indicator for the patent's originality (generality) score being in the top 1% among patents applied for in the same month. *VC-Backed* is an indicator variable equal to one if one of the patent assignees is a VC-backed firm as of the patent application date. A patent assignee is defined as being VC-backed as of the patent application date if it the patent application date is between the assignee's first VC financing round and its last VC financing round. *Recession* is an indicator variable equal to one if the U.S. was in a recession during the month the patent was applied for according to the NBER Business Cycle Dating Committee. *Early Stage* is an indicator variable equal to one if the patent assignee was seed stage or early stage as of its most recent VC financing round according to VentureXpert. *Late Stage* is an indicator variable equal to one if the patent assignee was not seed stage or early stage as of its most recent VC financing round. were not based in the U.S. *Patent Class FE* represent class fixed effects based on the patent's primary four-digit CPC classification. *Month FE* represent month fixed effects. *Patent Class X Month FE* represent patent class by month fixed effects. Standard errors are clustered by application month. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Top 1% Originality (Within Month)				Top 1% Generality (Within Month)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{1}$(Recession) × $\mathbb{1}$(VC-Backed)	-0.004**	-0.005**			-0.003	-0.004		
	(0.002)	(0.002)			(0.003)	(0.002)		
$\mathbb{1}$(VC-Backed)	0.012***	0.012***			0.015***	0.016***		
	(0.001)	(0.001)			(0.001)	(0.001)		
$\mathbb{1}$(Recession) × $\mathbb{1}$(VC-Backed and Early Stage)			-0.011***	-0.011***			-0.009***	-0.009***
			(0.003)	(0.003)			(0.003)	(0.003)
$\mathbb{1}$(VC-Backed and Early Stage)			0.014***	0.013***			0.024***	0.024***
			(0.002)	(0.002)			(0.002)	(0.002)
$\mathbb{1}$(Recession) × $\mathbb{1}$(VC-Backed and Late Stage)			-0.002	-0.002			-0.001	-0.002
			(0.003)	(0.002)			(0.003)	(0.003)
$\mathbb{1}$(VC-Backed and Late Stage)			0.011***	0.011***			0.012***	0.013***
			(0.001)	(0.001)			(0.001)	(0.001)
Patent Class FE	Yes	No	Yes	No	Yes	No	Yes	No
Month FE	Yes	No	Yes	No	Yes	No	Yes	No
Patent Class × Month FE	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.005	0.080	0.005	0.080	0.017	0.068	0.017	0.068
Observations	2,676,035	2,676,035	2,676,035	2,676,035	2,676,035	2,676,035	2,676,035	2,676,035

Table 5: Relationship Between Recessions and VC-Backed Patent Closeness to Science

This table shows the OLS relationship between recessions and VC-backed patent closeness to science. Observations are utility patents awarded between between January 1, 1976 and December 31, 2017 and assigned to a U.S. firm. The dependent variable in columns 1-4 (5-8) is an indicator for the patent's backward citations to academic research (published in top quartile journals) being in the top 1% among patents applied for in the same month. *VC-Backed* is an indicator variable equal to one if one of the patent assignees is a VC-backed firm as of the patent application date. A patent assignee is defined as being VC-backed as of the patent application date if it the patent application date is between the assignee's first VC financing round and its last VC financing round. *Recession* is an indicator variable equal to one if the U.S. was in a recession during the month the patent was applied for according to the NBER Business Cycle Dating Committee. *Early Stage* is an indicator variable equal to one if the patent assignee was seed stage or early stage as of its most recent VC financing round according to VentureXpert. *Late Stage* is an indicator variable equal to one if the patent assignee was not seed stage or early stage as of its most recent VC financing round. *Patent Class FE* represent class fixed effects based on the patent's primary four-digit CPC classification. *Month FE* represent month fixed effects. *Patent Class X Month FE* represent patent class by month fixed effects. Standard errors are clustered by application month. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Top 1% Closeness to Science (Within Month)				Top 1% Closeness to Quality Science (Within Month)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{1}$(Recession) × $\mathbb{1}$(VC-Backed)	-0.004**	-0.004**			-0.002	-0.003		
	(0.002)	(0.002)			(0.002)	(0.002)		
$\mathbb{1}$(VC-Backed)	0.010***	0.010***			0.009***	0.008***		
	(0.001)	(0.001)			(0.001)	(0.001)		
$\mathbb{1}$(Recession) × $\mathbb{1}$(VC-Backed and Early Stage)			-0.009***	-0.009***			-0.006*	-0.006*
			(0.003)	(0.003)			(0.003)	(0.003)
$\mathbb{1}$(VC-Backed and Early Stage)			0.015***	0.014***			0.015***	0.014***
			(0.002)	(0.002)			(0.002)	(0.002)
$\mathbb{1}$(Recession) × $\mathbb{1}$(VC-Backed and Late Stage)			-0.002	-0.001			-0.001	-0.001
			(0.002)	(0.002)			(0.002)	(0.002)
$\mathbb{1}$(VC-Backed and Late Stage)			0.008***	0.009***			0.006***	0.006***
			(0.001)	(0.001)			(0.001)	(0.001)
Patent Class FE	Yes	No	Yes	No	Yes	No	Yes	No
Month FE	Yes	No	Yes	No	Yes	No	Yes	No
Patent Class × Month FE	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.115	0.162	0.115	0.162	0.165	0.207	0.165	0.207
Observations	2,676,035	2,676,035	2,676,035	2,676,035	2,676,035	2,676,035	2,676,035	2,676,035

Table 6: Relationship Between Recessions and VC-Backed Patent Citations with Assignee Fixed Effects

This Table repeats the analysis of Table 3 with assignee fixed effects. Observations are utility patents awarded between between January 1, 1976 and December 31, 2017 and assigned to a U.S. firm. The dependent variable in columns 1-4 is an indicator for the number of forward cites being in the top 1% among patents applied for in the same month. The dependent variable in columns 5-8 is the log of one plus the total number of forward citations to the patent. *VC-Backed* is an indicator for the patent assignees being a VC-backed firm as of the patent application date. A patent assignee is defined as VC-backed as of the patent application date if it the patent application date is between the assignee's first VC financing round and its last VC financing round. *Recession* is an indicator variable for the U.S. being in a recession during the month the patent was applied for according to the NBER Business Cycle Dating Committee. *Early Stage* is an indicator for the patent assignee being seed or early stage as of its most recent VC financing round according to VentureXpert. *Late Stage* is an indicator for the patent assignee note being seed stage or early stage as of its most recent VC financing round. *Patent Class FE* represent class fixed effects based on the patent's primary four-digit CPC classification. *Month FE* represent month fixed effects. *Patent Class X Month FE* represent patent class by month fixed effects. Standard errors are clustered by application month. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Top 1% Cites (Within Month)				Log(1+Cites)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{1}$(Recession) × $\mathbb{1}$(VC-Backed)	-0.000	-0.001			-0.005	0.000		
	(0.002)	(0.002)			(0.015)	(0.014)		
$\mathbb{1}$(VC-Backed)	0.013***	0.012***			0.175***	0.138***		
	(0.001)	(0.001)			(0.010)	(0.010)		
$\mathbb{1}$(Recession) × $\mathbb{1}$(VC-Backed and Early Stage)			-0.004	-0.003			-0.034	-0.028
			(0.003)	(0.003)			(0.022)	(0.022)
$\mathbb{1}$(VC-Backed and Early Stage)			0.023***	0.022***			0.307***	0.266***
			(0.002)	(0.002)			(0.013)	(0.013)
$\mathbb{1}$(Recession) × $\mathbb{1}$(VC-Backed and Late Stage)			0.000	-0.000			-0.002	0.004
			(0.002)	(0.002)			(0.019)	(0.019)
$\mathbb{1}$(VC-Backed and Late Stage)			0.010***	0.010***			0.138***	0.102***
			(0.001)	(0.001)			(0.011)	(0.010)
Assignee FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Patent Class FE	Yes	No	Yes	No	Yes	No	Yes	No
Month FE	Yes	No	Yes	No	Yes	No	Yes	No
Patent Class × Month FE	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.173	0.222	0.173	0.222	0.391	0.451	0.391	0.451
Observations	2,241,808	2,241,808	2,241,808	2,241,808	2,241,808	2,241,808	2,241,808	2,241,808

Table 7: Monthly Venture Capital Activity in Recessions Relative to Other Times

This table shows how VC investment activity changes during recessions, using data from Refinitiv between January 1976 and March 2020. All columns use monthly data and OLS models. Recession periods are defined as the months during the NBER recession period (peak to trough). The mean of the indicator variable Recession is 0.127. In columns (1)-(4), the dependent variables are the number of VC deals; either all deals (1), early stage deals (2), late stage deals (3), or early minus late deals (4). In columns (5)-(8), the dependent variables are the log of the total amount of VC deals in real 2019 dollars; either all deals (5), early stage deals (6), late stage deals (7), or early minus late deals (8). The bottom row shows the means of the dependent variables during non-recession periods. Standard errors are robust. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent variable:	Number of VC Deals				Log Amount of VC			
	All	Early	Late	Early - Late	All	Early	Late	Early - Late
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{1}$(Recession)	-37.563*	-33.115***	-4.447	-28.668***	-0.329*	-0.391**	-0.257	-0.134
	(21.812)	(7.826)	(14.375)	(7.747)	(0.199)	(0.162)	(0.226)	(0.103)
Observations	533	533	533	533	533	533	533	533
R^2	0.005	0.017	0.000	0.025	0.003	0.006	0.001	0.001
Non Recession Mean	244.652	109.044	135.608	-26.564	14.031	12.828	13.570	-0.741

Table 8: Relationship Between Recessions and VC-Backed Patent Citations by Fundraising Timing

This table shows the OLS relationship between recessions and VC-backed patent citations by fundraising timing. Observations are utility patents awarded between between January 1, 1976 and December 31, 2017 and assigned to a U.S. firm. *Raised Outside Boom* indicates that the most recent round occurred either during the recession or prior to six months before the first month of the recession. *Raised During Boom* indicates that the most recent round occurred in the six months before the beginning of the recession. All other variables are as defined in Table 3. Standard errors are clustered by application month. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Top 1% Cites (Within Month)		Log(1+Cites)	
	(1)	(2)	(3)	(4)
$\mathbb{1}$(Recession) × $\mathbb{1}$(VC-Backed and Early Stage, Raised Outside Boom)	-0.008**	-0.008*	-0.130***	-0.094***
	(0.004)	(0.004)	(0.033)	(0.031)
$\mathbb{1}$(VC-Backed and Early Stage, Raised Outside Boom)	0.020***	0.021***	0.478***	0.451***
	(0.002)	(0.002)	(0.014)	(0.014)
$\mathbb{1}$(Recession) × $\mathbb{1}$(VC-Backed and Early Stage, Raised During Boom)	-0.003	-0.001	0.092	0.093
	(0.008)	(0.008)	(0.073)	(0.069)
$\mathbb{1}$(VC-Backed and Early Stage, Raised During Boom)	0.008	0.008	0.279***	0.270***
	(0.006)	(0.006)	(0.056)	(0.053)
$\mathbb{1}$(Recession) × $\mathbb{1}$(VC-Backed and Late Stage)	-0.003	-0.004	-0.005	0.006
	(0.003)	(0.003)	(0.032)	(0.031)
$\mathbb{1}$(VC-Backed and Late Stage)	0.012***	0.013***	0.337***	0.329***
	(0.001)	(0.001)	(0.010)	(0.010)
Patent Class FE	Yes	No	Yes	No
Month FE	Yes	No	Yes	No
Patent Class × Month FE	No	Yes	No	Yes
R^2	0.027	0.082	0.275	0.349
Observations	2,241,808	2,241,808	2,241,808	2,241,808

Table 9: Monthly Follow-On Venture Capital Activity in Recessions Relative to Other Times

This table shows how follow-on VC investment activity changes during recessions, using data from Refinitiv between January 1976 and March 2020. All columns use monthly data and OLS models. We define a "follow-on" deal as one in which the lead investor participated in a previous round of financing for the company. That is, these are deals in which the lead investor previously invested in that company. Observations are at the month level. Recession periods are defined as the months during the NBER recession period (peak to trough). The mean of the indicator variable Recession is 0.127. The dependent variables in columns (1)-(3) are the share of the number of VC deals that are follow-on deals; either the share of all deals (1), early stage deals (2), or late stage deals (3). The dependent variables in columns (1)-(3) are the share of the amount of VC investment that month that is follow-on; either the share of all deals (1), early stage deals (2), or late stage deals (3). The average company has 1.7 early deals. The bottom row shows the means of the dependent variables during non-recession periods. Standard errors are robust. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent variable:	Share of VC Deals that are Follow-on from Lead VC			Share of VC Deal Amount that is Follow-on from Lead VC		
	All	Within Early	Within Late	All	Within Early	Within Late
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$(Recession)	0.034**	0.021	0.034**	0.023*	0.021	0.058*
	(0.015)	(0.014)	(0.017)	(0.013)	(0.028)	(0.033)
Observations	533	533	533	533	533	533
R^2	0.009	0.004	0.007	0.005	0.000	0.003
Non Recession Mean	0.231	0.156	0.286	0.179	0.221	0.333

Appendix A Appendix

Table A.1: Relationship Between Recessions and VC-Backed Patent Citations—Robustness

This table repeats the analysis of Table 5 but using different cutoffs for top-cited patents. In columns 1–2 top-cited patents are defined as those in the top 10% of forward citations among patents from the same application year. In the remaining columns, top-cited patents are defined as those in the top 10% of forward citations among patents from the same application month (columns 3–4) or year (columns 5—6). *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Top 1% Cites (Within Year)		Top 10% Cites (Within Month)		Top 10% Cites (Within Year)	
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$(Recession) × $\mathbb{1}$(VC-Backed and Early Stage)	-0.010***	-0.009***	-0.042***	-0.036***	-0.038***	-0.032***
	(0.003)	(0.003)	(0.009)	(0.009)	(0.009)	(0.009)
$\mathbb{1}$(VC-Backed and Early Stage)	0.019***	0.020***	0.127***	0.124***	0.127***	0.124***
	(0.002)	(0.002)	(0.004)	(0.004)	(0.004)	(0.004)
$\mathbb{1}$(Recession) × $\mathbb{1}$(VC-Backed and Late Stage)	-0.003	-0.003	0.003	0.002	0.005	0.004
	(0.003)	(0.003)	(0.010)	(0.009)	(0.010)	(0.009)
$\mathbb{1}$(VC-Backed and Late Stage)	0.012***	0.013***	0.080***	0.081***	0.080***	0.081***
	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)	(0.003)
Patent Class FE	Yes	No	Yes	No	Yes	No
Month FE	Yes	No	Yes	No	Yes	No
Patent Class × Month FE	No	Yes	No	Yes	No	Yes
R^2	0.028	0.083	0.065	0.140	0.066	0.141
Observations	2,241,808	2,241,808	2,241,808	2,241,808	2,241,808	2,241,808

Table A.2: Recessions and Industry Share of VC Deals

This table shows the OLS relationship between recessions and the share of VC deals in a given industry, at the monthly level. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Share of All VC Deals that are							
Dependent variable:	Biotechnology	Medical & Health	Internet	Computer Hardware & Software	Communications & Media	Consumer Related	Industrial & Energy	Other
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{1}$(Recession)	-0.003	-0.006	-0.025	-0.014	0.001	-0.007	0.028***	0.030**
	(0.005)	(0.006)	(0.015)	(0.010)	(0.006)	(0.006)	(0.009)	(0.012)
Observations	533	533	533	533	533	533	533	533
R^2	0.001	0.001	0.004	0.002	0.000	0.002	0.013	0.008
Non Recession Mean	0.075	0.117	0.131	0.309	0.088	0.063	0.074	0.149

Table A.3: Monthly Early Stage Venture Capital Activity in Recessions Relative to Other Times, Omitting Particular Recessions and Periods

This table shows how VC investment activity changes during all but one of the recessions, using data from Refinitiv between January 1976 and March 2020. All columns use monthly data and OLS models. Recession periods are defined as the months during the NBER recession period (peak to trough). In each column of Panel A, we omit months corresponding to the recession identified in the column header. In each column of Panel B, we omit a particular set of years. The overall mean of the indicator variable Recession is 0.127. The bottom row shows the means of the dependent variables during non-recession periods. Standard errors are robust. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Omitting Particular Recessions

Dependent variable: Number of Early VC Deals					
Omitting Recession:	1980	1981-82	1990-91	2001	2007-09
	(1)	(2)	(3)	(4)	(5)
𝟙(Recession)	-25.184***	-16.794*	-28.627***	-40.419***	-57.176***
	(7.857)	(8.995)	(8.508)	(8.307)	(7.820)
Observations	527	517	525	525	515
R^2	0.009	0.003	0.012	0.023	0.037
Non Recession Mean	109.044	109.044	109.044	109.044	109.044

Panel B: Omitting Particular Periods

Dependent variable: Number of Early VC Deals					
Omitting:	1995-2002	1976-1990	1991-2019	1976-1984	2000-2019
	(1)	(2)	(3)	(4)	(5)
𝟙(Recession)	-36.263***	-25.056***	-8.756**	-20.579**	-27.966***
	(6.990)	(7.793)	(3.851)	(8.153)	(4.454)
Observations	549	353	292	425	400
R^2	0.028	0.009	0.012	0.006	0.032
Non Recession Mean	77.415	139.170	25.959	125.727	44.157