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ABSTRACT

By comparing patenting among VC-backed firms to the universe of U.S. patents over the period 1976-2019, we document that while patents led by VC-backed firms are of significantly higher quality and economic importance than the average patent, VC-backed innovation is substantially more procyclical than innovation in the broader economy. This is driven early-stage startups, whose innovation in recessions is relatively less cited, less original, less general, and less related to fundamental science. Our findings are most consistent with frictions in capital supply playing an important role, leading VCs to change their investment focus during downturns towards less innovative startups.

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1 Introduction

Interest in the contribution of venture capital (VC) to innovation has increased in recent years among both policymakers and academics. This renewed focus reflects two considerations. The first is the well-documented slowdown in developed-world productivity growth.[1] The second is the decline in basic research and in research efficiency at large corporations, which has traditionally accounted for the bulk of R&D expenditures (Arora, Belenzon, and Sheer 2019; Bloom et al. 2020). Against this backdrop, the ability of VC funds to stimulate innovation is increasingly relevant. The many billions of dollars that have been allocated to shore up venture-backed firms across the world since the onset of the COVID-19 crisis underscore the extent of policy interest in VC-driven innovation (Simpson 2020; CNBC 2020; Griffith and McCabe 2020; Parsa 2020; Ghosh 2020).

Despite the policy interest in VC—stemming in part from concerns about social costs from disruptions to VC-backed ventures during recessions—and well-known cyclicality of VC financing, we know remarkably little about how venture-backed *innovation* varies over the business cycle or how this relates to innovation in the broader economy. Cyclicality in VC investment may not be worrisome from an innovation standpoint. While investing activity declines, the quality of investment could improve. Indeed, there are anecdotal assertions that the quality of startups is higher during recessions.[2]

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 (Kortum and Lerner 2000; Puri and Zarutskie 2012). We examine whether the volume and quality of VC-backed innovation are higher or lower during

[1] Organisation for Economic Cooperation and Development (2020), "Productivity statistics," https://www.oecd.org/sdd/productivity-stats/.

[2] See, for instance, https://www.businessinsider.com/paul-graham-reasons-to-start-a-startup-recession-2020-3 and https://www.inc.com/anne-gherini/6-iconic-companies-that-succeeded-during-a-recession.html.

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. 2020).

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. The disproportionate decline in novelty and impact of VC-backed startups during recessions is 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.[3]

Why would early-stage VC-backed innovation be particularly sensitive to economic downturns? Potential mechanisms can be grouped into two broad categories. One is that investment opportunities for VCs are more cyclical relative to the broader economy. This is no doubt a factor, at least in particular recessions, but a second mechanism with substantial support in our data is that VCs' willingness to fund more novel innovation seems to decline during recessions. VCs 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 VCs financing less innovative firms rather than them pushing their existing portfolio companies to become less innovative.[4] 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 VCs 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 VCs with heavy exposure to information technology after the dot com collapse of the early

[3] 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.

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

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, VCs 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.[5]

Facing a need to conserve capital to fund existing portfolio companies and uncertainty about raising new funds from limited partners due to the unpredictable 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.[6]

These sources of capital constraints – fundraising uncertainty and pressure to support existing portfolio companies – can lead VCs 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.[7] Late-stage firms are more likely to be cash-

[5] https://www.fastcompany.com/90497989/we-literally-couldnt-fundraise-why-wealthy-vcs-wont-save-struggling-startups;
https://www.ft.com/content/3078d978-89f4-11df-bd30-00144feab49a
https://www.forbes.com/sites/donbutler/2020/03/17/this-downturn-will-be-different-what-we-expect-in-a-recession-marred-by-coronavirus/24ce7fb42cd7

[6] 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.

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

flow positive and should also benefit from VCs' strategy of shoring up existing portfolio companies in downturns, implying that they should be less affected during recessions. Consistent with these predictions, we show – to our knowledge for the first time – that early-stage VC deal activity declines on average by about 30% during recessions, while late-stage activity is relatively unaffected.

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 variation across industries. To explore this further, we consider the COVID-19 crisis, in which a recession occurred very suddenly. We document that VC activity fell precipitously during the initial phases of the COVID-19 crisis and once again the pattern was driven by early-stage deals. Relative to the five months before March 4, 2020, weekly early-stage VC deals declined by 34% during the four months that followed. In contrast, late-stage VC remained much more robust. Moreover, as with prior recessions, declines did not appear to be driven by shifts in technological opportunities. Indeed, comparing relative declines in VC activity with sector-level declines in the public market shows no meaningful correlation. In sum, while they do not suggest that other channels are unimportant, our results point to constraints in the supply of capital playing a crucial role in the cyclicality of VC-backed innovation.

Overall, our paper helps to shed light on the nature of innovation in downturns, which has long been puzzling to researchers. 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; 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, Haltiwanger et al. 1993; Aghion and Saint-Paul 1998). Manso, Balsmeier, and

Fleming (2019) use data on public firms to show that in recessions, firm innovation shifts away from exploitation, which yields short-term profits, towards exploratory work, which will be more useful in the long term.

On the other hand, a large empirical literature beginning with Griliches (1984) finds that overall innovation is pro-cyclical. This can emerge from counter-cyclical markup variations (Comin and Gertler 2006). Alternatively, Barlevy (2007) and Fabrizio and Tsolmon (2014) suggest the channel of reduced ability to profit from commercializing ideas before competitors copy the insights. Studying individual inventors, Bernstein, McQuade, and Townsend (2020) find that household financial distress deters risky innovation, and Babina, Bernstein, and Mezzanotti (2020) find that independent invention declined during the Great Depression. Related to the mechanism of capital supply, Moreira and Granja (2020) argue that financing constraints lead consumer goods firms to introduce fewer novel products during recessions. Our results complement these findings. We demonstrate that during recessions, there is a shift away from high-quality innovation among VC-backed startups, apparently because of changes in the types of firms that VCs are willing to finance.

More broadly, we contribute to this debate by highlighting the role of VC-backed startups. As we and others document, VC-backed startups are disproportionately important to economy-wide innovation, long-term job creation, and value formation. Yet much of the literature on the cyclicality of innovation focuses on publicly traded firms or individual inventors. VC-backed firms, particularly those receiving their first early-stage investment, do not necessarily have the luxury of shifting their innovation investments or types of innovation across the business cycle. We provide the first evidence that, contrary to a common narrative in which VC investment and VC-backed startups are relatively insulated from downturns, deal activity is in fact highly pro-cyclical, and more importantly, the relative quality of innovation declines more for VC-backed firms than for other types of firms during downturns.

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). Finally, our findings relate to the literature 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 2019).

2 Data

Our analysis of VC-backed innovation relative to the universe of innovation in the U.S. makes use of several datasets.

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.[8] 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

[8]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 (from the same year), 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.[9] 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

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

if it influences subsequent innovations in many different areas. This measure is defined 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 (2019).

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 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 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.[10] 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.

3.2 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 1 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 ($\mathbb{1}(\text{Recession}_t)$) 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 peak to the trough as identified by the NBER). $\mathbb{1}(VCBacked_{ict})$ is an indicator equal to

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

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 regression does as well as logit 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.[11]

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. This means that the probability of a VC-backed patent being in the top percentile is

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

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 2.5x 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 do not reflect something spurious about 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 2.2x more likely to be in the right tail of the originality distribution during normal times but only 1.7x 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 2x more likely to be in the right tail of the closeness to science distribution during normal times but only 1.6x 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 VCs 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 VCs 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 VCs view deal selection as being more important to their role than post-investment monitoring activities (Gompers et al. 2020a). 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.

3.3 Venture Capital Investment in Prior 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.[12] 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 (column 4). This pattern also holds 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

[12]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 2 plots the number of venture deals, the S&P 500 index, and NBER recessions.

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).[13] In sum, there is a consistent decline in early-stage VC deals during recessions, which to our knowledge has not been documented before.

3.4 Change in Investment Opportunities vs. Change in 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 VCs; that is, a change in the selection of deals by VCs. 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, perhaps surprisingly, 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, equivalently, 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 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

[13] 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.

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 and VCs tend to 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 VCs 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 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."[14]

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 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

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

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.

Finally, a version of the demand channel is that entrepreneur entry declines during recessions, perhaps because of changing risk preferences. This could certainly be part of the story. However, the finding that cross-sectional variation in fundraising timing is a significant source of heterogeneity (Table 8) is inconsistent with this mechanism, because it conditions on entry. Historically, Babina (2020) provides microeconomic evidence showing that firm distress leads employees to depart to start new firms, potentially increasing the supply of entrepreneurs during these times. Below, we discuss this possibility further using the sudden onset of the COVID-19 recession. Overall, the historical results are, perhaps surprisingly, less consistent with market opportunities or demand channels than with a capital supply channel.

4 The COVID-19 Recession

Of course, our ability to show causal evidence of shifts in VC supply is limited by the nature of economic cycles, in which overall market activity usually shifts gradually and reflects market factors that may be endogenous to VC investment opportunities. To provide additional evidence of the plausibility of the capital supply channel, we therefore look at VC financing in the immediate aftermath of the COVID-19 pandemic reaching the U.S. While the innovation outcomes will not be observable for some years, the pandemic offers an interesting "out of sample" analysis related to VC financing. Moreover, because it occurred too immediately and discontinuously to plausibly reflect changes in new startups seeking funding, it is also arguably exogenous to the supply of innovation and entrepreneurs, particularly in the short term. Of course, at the same time, the COVID-19 recession brings its own particularities. For example, the greater difficulty of meeting in person may affect deal-making, especially at the earliest stages. We discuss this possibility below.

4.1 Sources for the COVID-19 Analysis

To analyze how VC deal activity responded to the COVID-19 pandemic and attendant economic crisis, we use data from Pitchbook, CB Insights, and Capital IQ. We tabulate VC investment deals in U.S.-based startups by industry and sector using the Pitchbook and CB Insights data. Pitchbook has the advantage of broader coverage, while CB Insights has detailed company descriptions, which enable us to assess changes in financing for particular types of businesses in sectors especially hard-hit by the crisis. For both datasets, we restrict the analysis to deals identified in the data as VC, excluding angel investments, buyouts, grants, and other types of financing that appear in the data. We then divide VC deals into either early- or late-stage, using the classifications provided. As above, early-stage deals are defined as Seed, Series A, or Series B, while late-stage deals are defined as all VC rounds that are Series C or later.

4.2 Number of Deals by Stage

In Figure 3, we show (using data from Pitchbook) that there has been a marked decline in VC deals since the onset of the crisis. We present deal activity aggregated by week between the weeks starting October 28, 2019 and June 15, 2020. Each week begins on the date identified on the x-axis. As there is in general substantial week-to-week fluctuation in the number of deals, we show a biweekly rolling mean, such that each point represents the mean taken over that week and the previous week. We identify the start of the COVID-19 crisis to be the week of March 4, 2020, which was the week in which the vast majority of U.S. states reported their first cases, confirmed U.S. cases passed the 1,000 mark, the most affected areas first closed schools, and deaths from community transmission were first reported.[15] We focus on the number of deals for two reasons. First, we are ultimately interested in how downturns affect the nature of VC-backed innovation. We anticipate that innovation is most closely related to the number of new firms being funded, rather than their valuations. Using the amount of financing leads the analysis to be dominated by a small number of large deals. Second, amounts are only reported for a selected subset of deals, leading us to be concerned about potential biases.

The top-left graph of Figure 3 shows that early-stage VC deals declined from an average of 114 deals per week before the crisis to 75 deals per week on average in the two months after the crisis, representing a decline of 34%. As there is some seasonality to VC activity, particularly around the beginning of the year, it is useful to compare these trends to the previous year. The bottom-left graph shows a dramatic decline in early-stage deals after subtracting the previous year's deals during the same week. In the right graphs, we consider late-stage VC deals. Consistent with our findings using the historical data, we find the effect of the crisis for late-stage deals is substantially muted.

While in the future the number of deals that Pitchbook reports in a given week may rise due to backfilling, this cannot explain the large discontinuity we observe in early March. We are comforted by the fact that Pitchbook reports similar patterns in its own analysis. For example, one analyst report in July 2020 concluded "Venture deal activity slowed in the second quarter...a 23.2% decline in deal count compared to Q1 2020...completed seed deals saw a massive slowdown in Q2...Investors have also doubled down on portfolio companies as follow-on financing activity heavily outweighed first-time financings during Q2. Unexpectedly, there has not been a drop in late-stage activity" (Pitchbook 2020).[16] At the end of 2020, it was clear that while overall VC deal-making was resilient in 2020,

[15] Based on the dates reported in https://en.wikipedia.org, "Timeline of the 2020 Coronavirus Pandemic in the United States."

[16] Further supporting our conclusion, we also observe a decline using data from CB Insights.

this was driven by deals for later-stage existing portfolio companies. Pitchbook's end-of-year report noted that "Much of [2020] funding activity can be attributed to the fat checks investors wrote for their existing, later-stage portfolio companies better suited to survive the worst of the pandemic. That didn't bode well for early-stage investments, which have dropped off significantly this year."[17]

4.3 Sector-Level Correlation with Stock Market Response

The fact that late-stage activity does not decline is suggestive that anticipated demand cannot be the main driver of the results we see in these charts. We further explore this hypothesis by examining whether the stock market and the VC market responded similarly to the crisis, specifically at the sector level. As Baker et al. (2020) show, COVID-19 had an immediate and massive impact on the stock market. In an analysis of public firms during the COVID-19 crisis, Hassan et al. (2020) conclude that "firms' primary concerns relate to the collapse of demand, increased uncertainty, and disruption in supply chains...financing concerns are mentioned relatively rarely." If the decline in VC investment we see is similarly driven primarily by anticipated changes in demand for a startups' goods and services, we would expect that the sectors worst hit in the public markets would also experience the greatest decline in VC activity.

To understand the correlation between the stock market and VC response at the sector level, we first examine the hardest-hit sectors among public companies whose stock is traded on the major U.S. exchanges. We gather from Capital IQ company-specific raw returns for the five days in March 2020 in which the stock market experienced significant losses: March 9, March 11, March 12, March 16, and March 18. While the stock market rose in the subsequent months, the sector dynamics remained similar over time, so that the hardest-hit sectors (e.g. airlines) remained depressed relative to less affected sectors

[17] https://pitchbook.com/news/articles/2020-vc-in-charts

(e.g. Internet). We are most interested in the relative changes across industries, which are quite consistent over a longer period.

We then aggregate the mean abnormal returns up to the six-digit GICS sector, weighting each company by its market capitalization on the relevant date. Maintained by MSCI and S&P Dow Jones, the GICS ("Global Industry Classification Standard") scheme assigns firms to sectors that are designed to capture present-day industries. We use the 2018 sector assignment, which is the most recent available.[18] We focus on the six-digit level, which has enough granularity to capture key differences in the degree to which a sector was affected by COVID-19. Our findings are not sensitive to value-weighting or using abnormal rather than raw returns.

The resulting sector-specific raw returns are shown in Appendix Figure A.1. As one might expect, the hardest-hit sectors are in transportation (including airlines), energy (especially oil and gas), and "Hotels, Restaurants, and Leisure." The least affected sectors are "Internet & Direct Marketing Retail," pharmaceuticals and biotech, household products, including food and beverages, and sectors related to communications, entertainment, and interactive media.

To compare stock market returns to VC activity, we map the GICS sectors to industries in CB Insights. We focus on identifying VC-backed startups within quartiles of sectors divided by their raw returns. That is, we divide the sectors in Appendix Figure A.1 into four quartiles ranging from most to least affected. Then we assign each VC-backed firm in CB Insights to one of the four quartiles of sectors. We include all VC-backed startups in CB Insights. We use existing industry categorizations and text descriptions about the company to identify businesses type. For example, for the industry "Hotels, Restaurants & Leisure," we use words such as "vacation," "hospitality," and "dining."[19]

[18]For more information, see https://www.msci.com/gics.

[19]There are a variety of subtle classification issues, as when a company selling airline tickets online could potentially be assigned to "Internet & Direct Marketing Retail," while a company providing restaurant software could be assigned to "Professional Services." Complete documentation of the categorization is available upon request.

In Figure 4, the navy-blue bars, representing the market returns, are arranged from least affected quartile (1) to most affected (4). We then compare the percent change in market returns by quartile to the percent change in VC deal volume. The green bars show the change in VC deal activity in the immediate weeks after the crisis by quartile. Surprisingly, the green bars indicate a broad-based decline in venture activity across both the sectors more and less affected in the public market.[20]

We reach similar conclusions in an industry-by-industry comparison with Pitchbook data. We match each six-digit GICS sector to a two-digit Pitchbook sector.[21] The left graph of Appendix Figure A.2 plots the stock market returns, again as described above, categorized by two-digit Pitchbook sectors. The right graph plots the percent change in early-stage VC deals. Both are arranged in descending order. The graphs demonstrate little correlation between sectors most affected in the public markets and those most affected in the VC market. In unreported tests, we confirm that this relationship holds at the four-digit Pitchbook level as well. With 139 four-digit industries, we find a correlation of an insignificant 0.03 between the change in stock market returns and the change in early VC deals. This exercise suggests that VC sensitivity to the crisis was not only driven by demand changes for startups' goods and services.

4.4 VC Accounts and Survey Evidence

Our final evidence on the role of the capital supply channel comes from contemporaneous accounts about and from VC investors themselves. The popular and industry press commonly cite conserving capital to fund existing portfolio companies as a central reason that investment in new startups falls during recessions. For example,

[20]Note that because we include late-stage deals, which experience a smaller decline, the average decline is less than the average early-stage decline.

[21]These sectors are relatively better suited to this exercise than the CB Insights sectors, and also allow us to demonstrate the same pattern using a different data source. The downside of the Pitchbook data is that we cannot employ company descriptions.

one article explains that, "As the virus took hold in February, VC firms shifted their operations into 'triage' mode, where helping existing investments survive the crisis became the name of the game."[22]

More formally, Gompers et al. (2020b) survey over 1,000 VCs about how COVID-19 has affected their decisions and investments. Survey respondents report having slowed their investment pace by 29% in the first half of 2020. Moreover, consistent with a capital supply channel, approximately 44% cite either "conserving dry powder" or "focusing on startups closer to profitability" as their primary reason for making fewer investments.

A final point concerns the possibility that VCs or entrepreneurs were unwilling to do deals without meeting in person. This could have played a role, but several pieces of evidence suggest it is not the main explanation. First, in this case we would expect at least some attenuated effect for first-time investments at later stages, which we do not. Second, VCs have reported going for walks with entrepreneurs to meet them.[23] While not all VCs are co-located with their portfolio companies, a very large proportion are in the same city. For example, Chen et al. (2010) show that VC-backed firms typically have at least one investor in the same metro region. Cumming and Dai (2010) also find strong local bias in VC investments, with the average distance between a company and its venture investor being less than 200 miles. Overall, it seems unlikely that the difficulty of meeting in person could explain the persistent trends we observe.

[22]https://www.fastcompany.com/90497989/we-literally-couldnt-fundraise-why-wealthy-vcs-wont-save-struggling-startups?ref=hvper.com&utm_source=hvper.comutm_medium=website.
https://www.ft.com/content/3078d978-89f4-11df-bd30-00144feab49a
https://www.forbes.com/sites/donbutler/2020/03/17/this-downturn-will-be-different-what-we-expect-in-a-recession-marred-by-coronavirus/24ce7fb42cd7

[23]For example, see https://medium.com/wharton-fintech/frank-rotman-founding-partner-at-qed-investors-past-present-and-future-of-fintech-ab4f94650732.

5 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 VCs 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 VCs 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 extremely pro-cyclical early-stage VC investments as an important area of future inquiry.

References

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. 2020. "Fencing off Silicon Valley: Cross-border venture capital and technology spillovers." Unpublished Working Paper.

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

Arora, Ashish, Sharon Belenzon, and Lia Sheer. 2019. "Back to basics: Why do firms invest in scientific research?" Unpublished Working Paper.

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. 2020. "Destructive creation at work: How financial distress spurs entrepreneurship." *Review of Financial Studies* forthcoming.

Babina, Tania, Asaf Bernstein, and Filippo Mezzanotti. 2020. "Crisis Innovation." Unpublished Working Paper.

Baker, Scott, Nicholas Bloom, Steven J. Davis, Kyle Kost, Marco Sammon, and Tasaneeya Viratyosin. 2020. "The unprecedented stock market reaction to COVID-19." *Covid Economics: Vetted and Real-Time Papers* 1 (3).

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. 2020. "Does economic insecurity affect employee innovation?" *Journal of Finance* forthcoming.

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.

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.

Chen, Henry, Paul Gompers, Anna Kovner, and Josh Lerner. 2010. "Buy local? The geography of venture capital." *Journal of Urban Economics* 67 (1):90–102.

CNBC. 2020. "Europe races to rescue its tech industry as start-ups fight for survival." *CNBC* .

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

Cooper, Russell, John Haltiwanger et al. 1993. "The Aggregate Implications of Machine Replacement: Theory and Evidence." *American Economic Review* 83 (3):360–382.

Cumming, Douglas and Na Dai. 2010. "Local bias in venture capital investments." *Journal of Empirical Finance* 17 (3):362–380.

Ewens, Michael, Alexander S Gorbenko, and Arthur Korteweg. 2019. "Venture capital contracts." Unpublished Working Paper.

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.

Ghosh, Shona. 2020. "The UK has greenlit a $300 million package to try to save thousands of startups from collapse during the COVID-19 pandemic." Business Insider.

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

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

Gompers, Paul A., Will Gornall, Steven N. Kaplan, and Ilya A. Strebulaev. 2020b. "Venture capitalists and COVID-19." *Working Paper* .

Griffith, Erin and David McCabe. 2020. "Start-Ups Pursue Free Money With Relief Funds, Prompting Backlash." The New York Times.

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 and D: Is There a Lag?” *International Economic Review* :265–283.

Hassan, Tarek A., Stephan Hollander, Laurence van Lent, and Ahmed Tahoun. 2020. “Firm-level exposure to epidemic diseases: Covid-19, SARS, and H1N1.” Unpublished Working Paper.

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* :674–692.

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

Manso, Gustavo, Benjamin Balsmeier, and Lee Fleming. 2019. “Heterogeneous innovation and the antifragile economy.” Unpublished Working Paper.

Marx, Matt and Aaron Fuegi. 2019. “Reliance on science: Worldwide front-page patent citations to scientific articles.”

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. 2020. “Product Innovation and Credit Market Disruptions.” Unpublished Working Paper.

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.

Parsa, Ali. 2020. “Letter to the Chancellor.” *https://www.scribd.com/document/455681169/Letter-to-the-Chancellor* .

Pitchbook. 2020. “Venture Capital Fundraising and Investment Dollars Remained Healthy Through 1H 2020 Amid Slowdown in Exits and Deal Count Due to Impacts of COVID-19.” Pitchbook Press Release, July 14.

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.

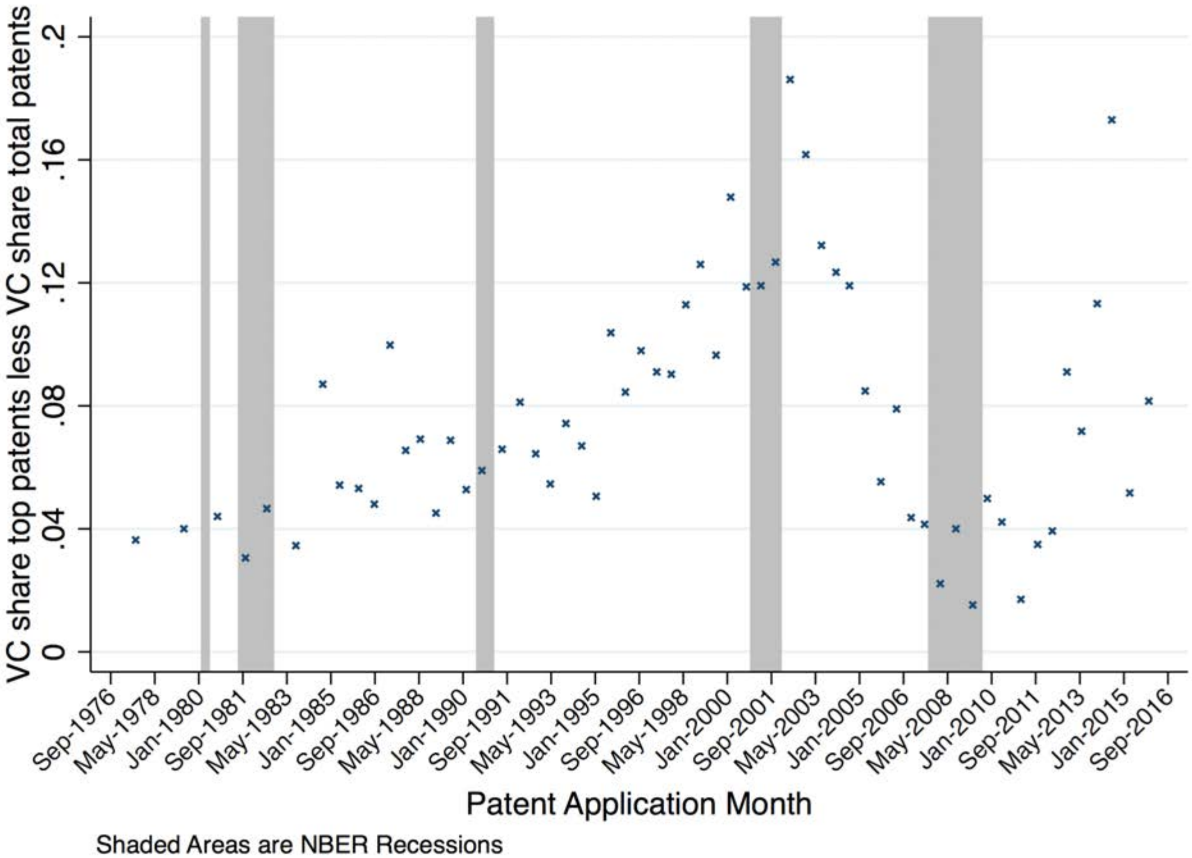
Robinson, David T. and Berk A. Sensoy. 2016. “Cyclicality, performance measurement, and cash flow liquidity in private equity.” *Journal of Financial Economics* 122 (3):521–543.

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

Simpson, Meghan. 2020. “BDC launches matching investment program for Canadian VC-backed Companies affected by COVID-10.” *Betakit* .

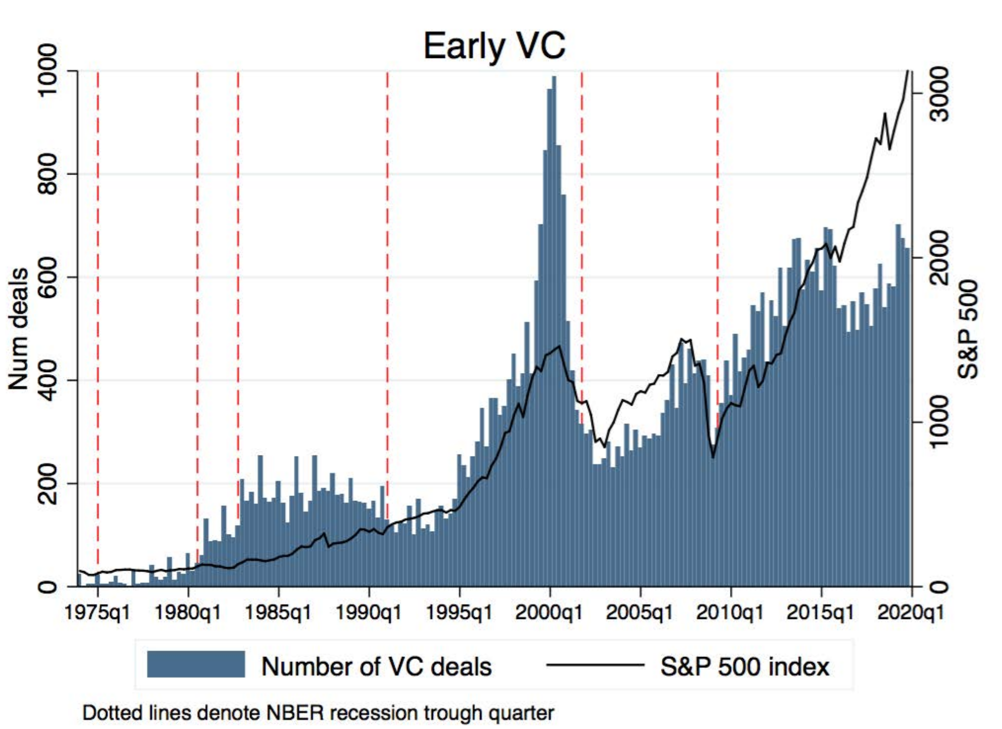
Townsend, Richard R. 2015. “Propagation of financial shocks: The case of venture capital.” *Management Science* 61 (11):2782–2802.

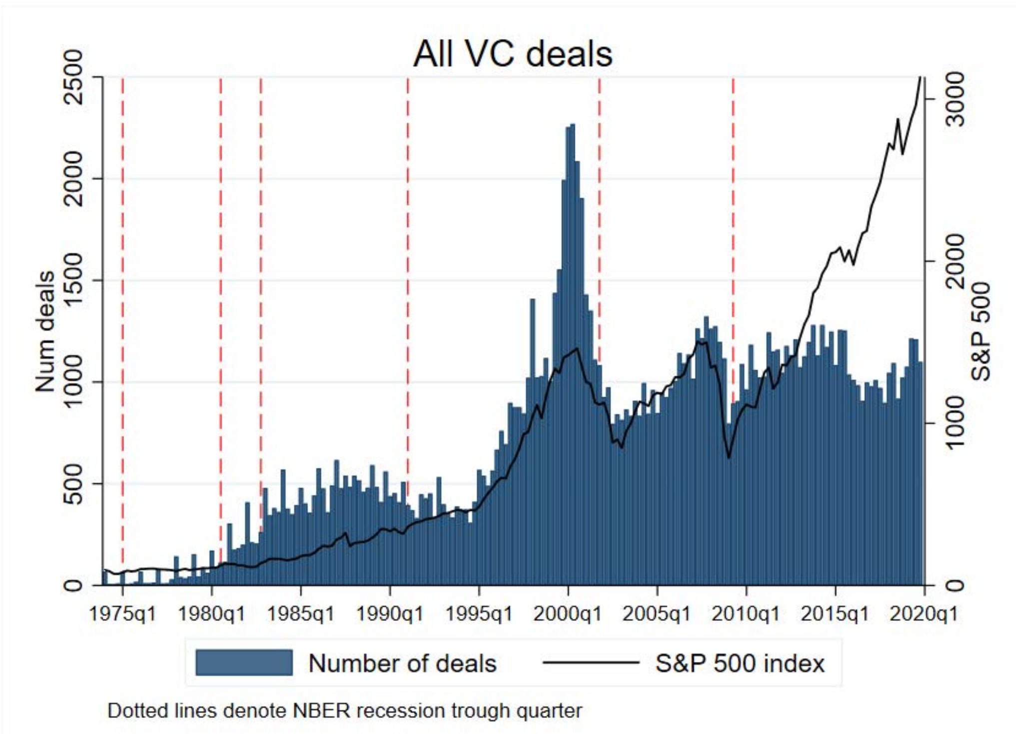
Figure 1: VC-backed Startup Share of Top Quality Patents Less VC share of Total Patents



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.

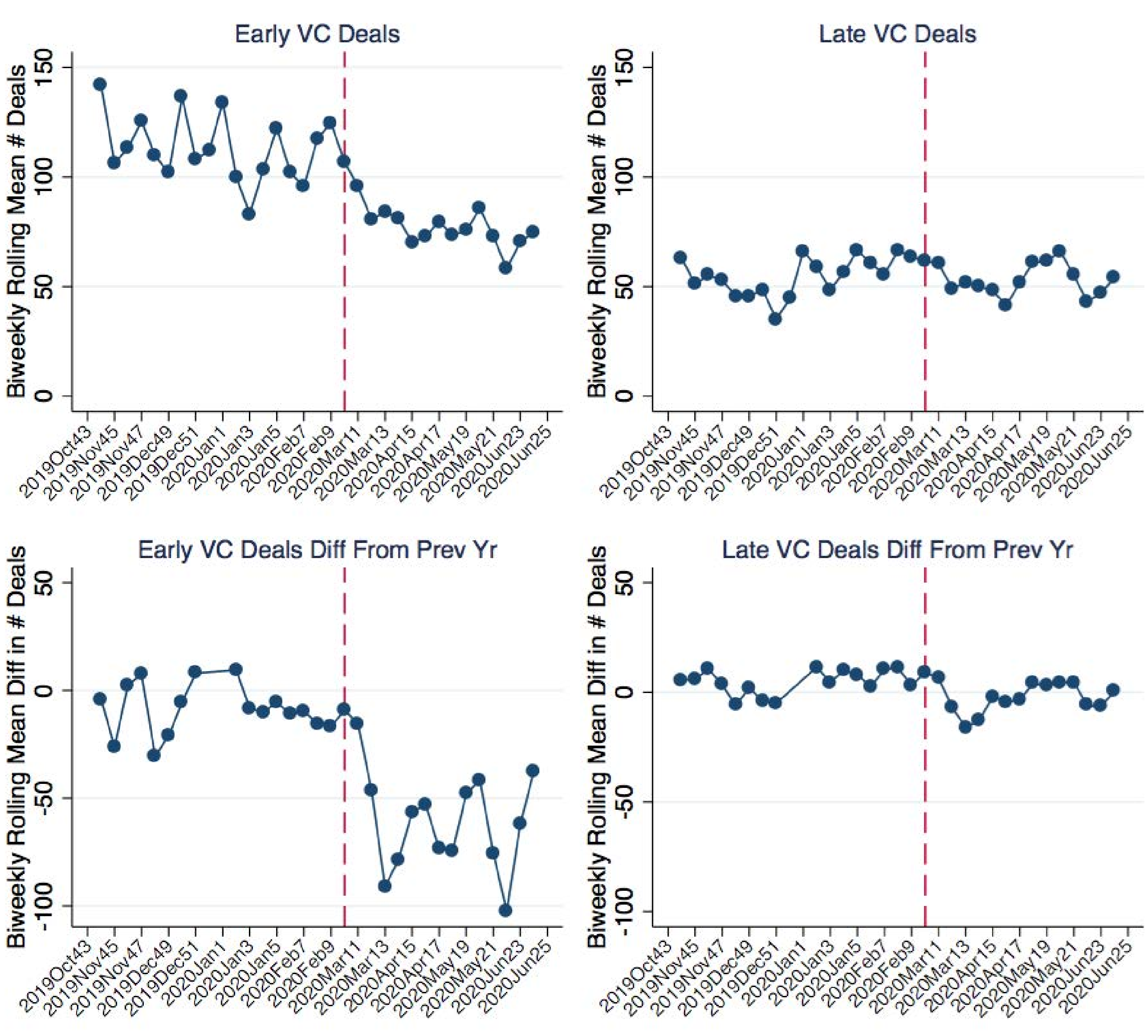
Figure 2: VC Investment and Market Cycles





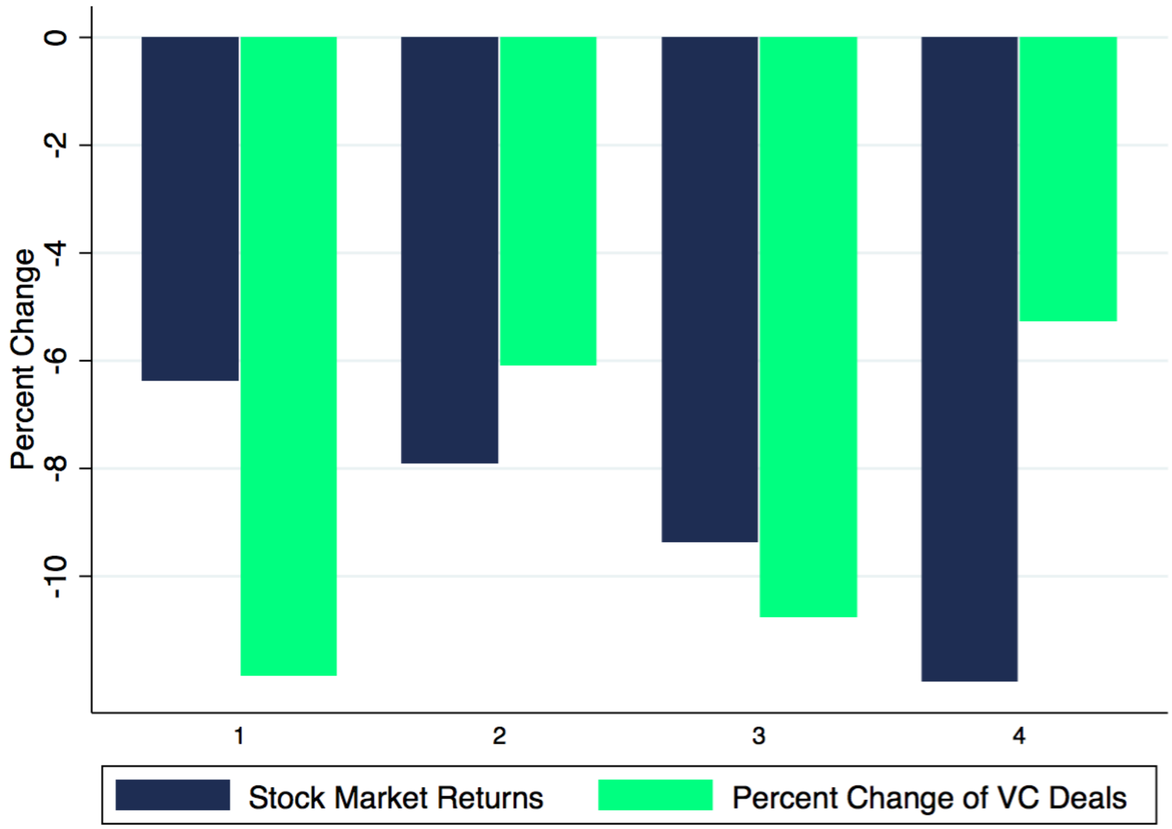
These figures show the quarterly number of VC deals. The top graph shows only early VC deals, while the bottom graph shows all VC deals. The red lines represent NBER recession trough quarters. The black line represents the stock market S&P 500 index. Source: VentureXpert.)

Figure 3: US VC Deals Around COVID-19 Crisis by Stage (Pitchbook)



These figures show the number of US VC deals by investment stage using data from Pitchbook. Frequency is weekly, and the first day of the week is shown on the x-axis. Each point represents a biweekly rolling mean, which is the mean taken over this week and the previous week. The red line at the first week of March 2020 represents the start (roughly) of the COVID-19 crisis in the U.S. Graphs on the top show the raw number of deals in the week; those on the bottom, the number of deals in the week less the number in the same week of the previous year. Source: Pitchbook.

Figure 4: Comparison of Change in VC and Stock Market Returns by Quartile of Stock Market Returns during COVID-19 Crisis



This figure compares across sectors how VC and stock markets have changed since the onset of the COVID crisis. First, we calculate value-weighted stock market returns for the five worst days in March across six-digit GICS sectors. We then divide the sectors into quartiles ranging from worst-hit (quartile 4), to least affected (quartile 1). The dark blue bars show the average daily stock market returns for each quartile of sectors. We map the GICS sectors to industries in CB Insights, using existing industry categorizations and text descriptions about the company to identify businesses type. We then compare the weekly number of deals before and after the inception of the COVID crisis. The pre-COVID period is from October 1, 2019 to March 1, 2020, and the post-COVID period is March 2-April 1, 2020. We calculate the percent change in average number of weekly deals in the two periods, shown in the green bars.

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) $\times$ $\mathbb{1}$(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) $\times$ $\mathbb{1}$(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) $\times$ $\mathbb{1}$(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 $\times$ 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.

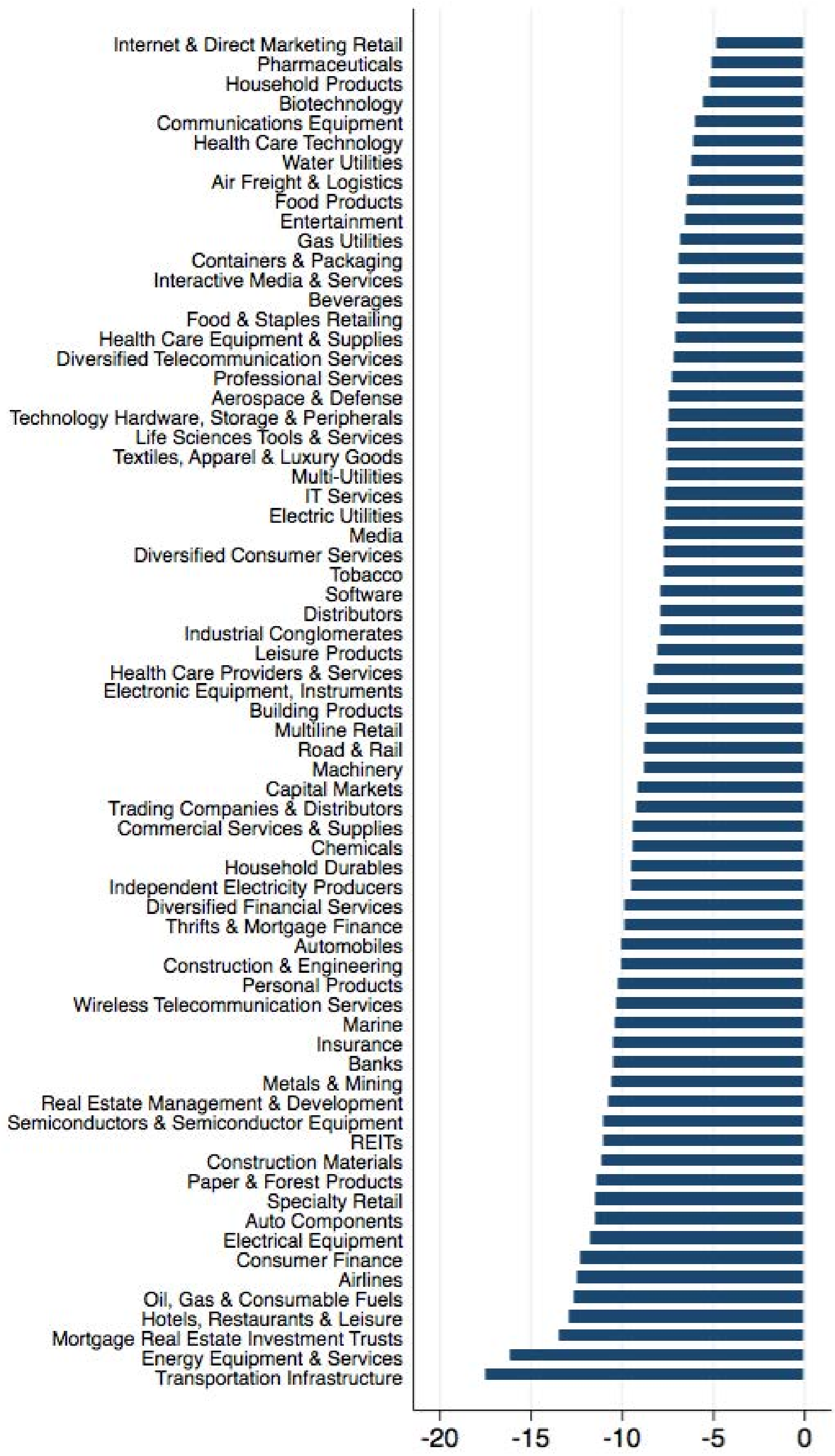
Panel A: Omitting Particular Recessions

Dependent variable: Number of Early VC Deals					
Omitting Recession:	1980	1981-82	1990-91	2001	2007-09
	(1)	(2)	(3)	(4)	(5)
$\mathbb{1}$(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

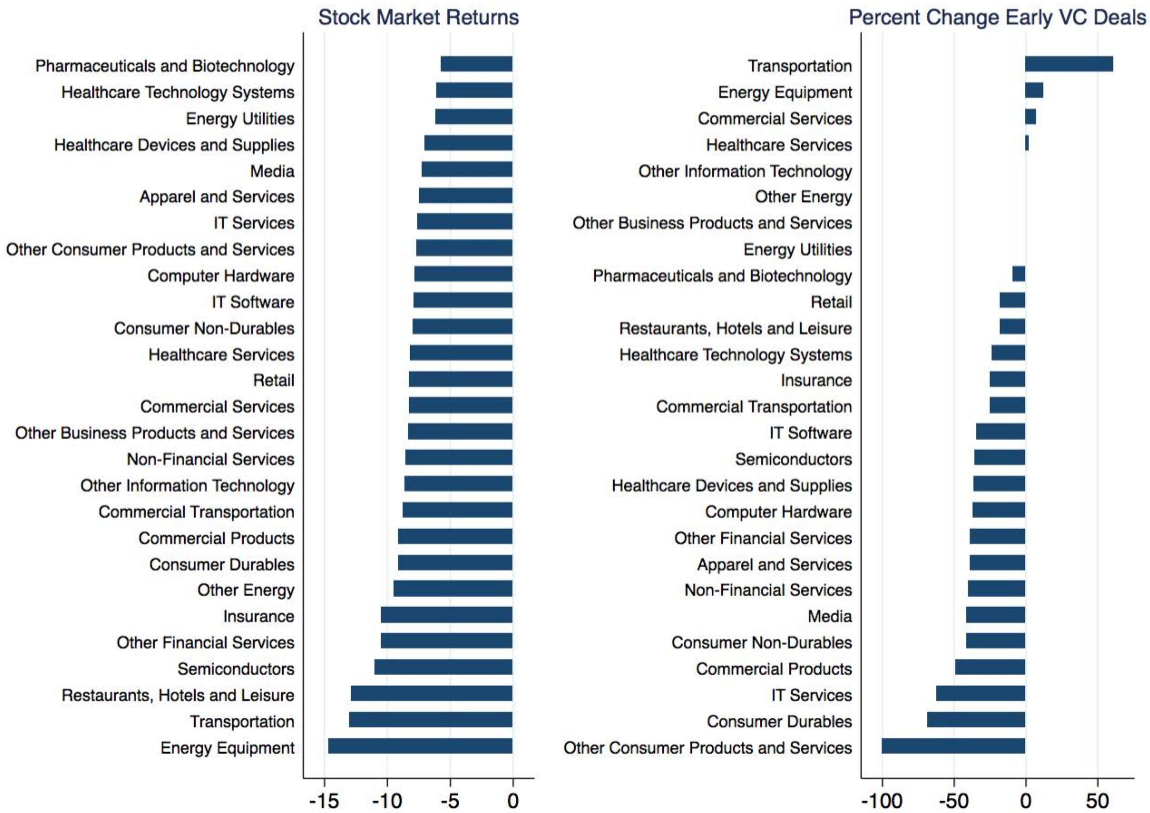
Dependent variable: Number of Early VC Deals					
Omitting:	1995-2002	1976-1990	1991-2019	1976-1984	2000-2019
	(1)	(2)	(3)	(4)	(5)
$\mathbb{1}$(Recession)	-36.263***	-25.056***	-8.756**	-20.579**	-27.966***
	(6.990)	(7.793)	(3.851)	(8.153)	(4.454)
Observations	549	353	292	425	400
R^2	0.028	0.009	0.012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

Figure A.1: Market Returns



This figure shows the average daily value-weighted returns by six-digit GICS sector across the five days in March 2020 with the largest drops in the S&P 500. Source: Datastream.

Figure A.2: Market Returns and Change in Early VC Investment



This figure compares stock market COVID-19 reactions to changes around COVID-19 in VC deal activity. The left figure shows the average daily value-weighted returns by six-digit GICS sector mapped to two-digit Pitchbook industry codes across the five days in March 2020 with the largest drops in the S&P 500. The right figure shows the percent change in VC deal volume after relative to before the COVID-19 crisis, which is identified as beginning the week starting March 4. The pre-period is October 28, 2019 to March 3, 2020. The post-period is March 4 to April 27, 2020. Source: Pitchbook, Datastream.