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HOW VENTURE CAPITAL FOLLOWS THE ECONOMY DOWN AND CURTAILS INNOVATION

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ABSTRACT

Although late-stage venture capital (VC) activity did not change dramatically in the first two months after the COVID-19 pandemic reached the U.S., early-stage VC activity declined by 38%. The particular sensitivity of early-stage VC investment to market conditions—which we show to be common across recessions spanning four decades from 1976 to 2017—raises questions about the pro-cyclicality of VC and its implications for innovation, especially in light of the common narrative that VC is relatively insulated from public markets. We find that the implications for innovation are not benign: innovation conducted by VC-backed firms in recessions is less highly cited, less original, less general, and less closely related to fundamental science. These effects are more pronounced for startups financed by early-stage venture funds. Given the important role that VC plays in financing breakthrough innovations in the economy, our findings have implications for the broader discussion on the nature of innovation across business cycles

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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 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 (Kortum and Lerner 2000; Bernstein, Giroud, and Townsend 2016). The many billions of dollars that have been allocated to shore up venture-backed firms in Canada, France, Germany, the United Kingdom, and many other nations since the onset of the COVID-19 crisis, which has not been without controversy, underscore the extent of policy interest in VC-driven innovation.[2]

We find that U.S. VC activity fell precipitously during the initial phases of the coronavirus disease 2019 (COVID-19) crisis, despite government efforts to prop up startups. In unpacking the source of this decline, we find that the number of weekly early-stage VC deals declined by nearly 38% in the two months starting March 4, 2020, relative to the previous four months. In contrast, later-stage VC has remained much more robust thus far. This higher sensitivity in *early-stage* VC is noteworthy, as the 10-year fund structure and the private, long-term nature of venture investments might suggest that VC deal activity—particularly at the early stages—is relatively insulated from downturns. Indeed, a low correlation with public markets has been an important justification for institutional

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

[2] For example, see:
https://www.nytimes.com/2020/04/27/technology/startups-sba-loans-backlash.html,
https://www.cnbc.com/2020/04/02/coronavirus-europe-races-to-rescue-tech-startups.html;
https://betakit.com/bdc-launches-matching-investment-program-for-canadian-vc-backed-companies/,
https://www.scribd.com/document/455681169/Letter-to-the-Chancellor, and
https://www.businessinsider.com/uk-future-fund-government-loans-startups-coronavirus-2020-4.

asset allocation to this sector, and a frequent claim of VC fund managers.[3] In theory, lower valuations and more investor bargaining power could even create good buying opportunities, potentially leading to a rise in venture investment during downturns.

Yet, we find the COVID-19 crisis is not an anomaly in this regard. Examining historical data on VC investment activity, we document that aggregate deal volume, capital invested, and deal size all decline substantially in recessions. Moreover, we find systematic evidence that investors who specialize in early-stage deals are significantly more responsive to business cycles than later-stage investors. This finding relates to existing evidence that private markets are characterized by pro-cyclical shifts in the levels of cash flows into and out of funds, transaction sizes, and valuations (Kaplan and Schoar 2005; Gompers et al. 2008; Robinson and Sensoy 2016), although to our knowledge the particular sensitivity of early-stage investors to business cycles has not been examined or documented before.

While the general boom and bust pattern within VC is well known, it may be that these patterns are not worrisome from an innovation standpoint; while investing activity declines, the quality of investment may improve. Indeed, there is anecdotal evidence that the quality of startups is higher during recessions.[4]

In the main contribution of this paper, we examine whether the volume and quality of VC-backed innovation is higher or lower during recessions, and the potential reasons for these patterns. To shed light on these questions, we use data on VC financing matched to the patenting of VC-backed startups over the period from 1976 to 2017. An important difference in our analysis from most prior work on VC and innovation in that we examine all U.S. patents, thereby comparing innovation by VC backed firms to innovation conducted more broadly in the economy. Our study of how VC-backed innovation has

[3] Two of many examples include https://www.foundational.nyc/insights/how-venture-capital-will-be-impacted-by-the-next-recession/ and https://citywire.co.uk/wealth-manager/news/private-equity-investments-can-offer-potential-for-counter-cyclical-returns/a952314.

[4] 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.

evolved relative to the broader economy over macro-economic cycles in this time period reveals four 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, 29.4% 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 4.7% are in the 1% most highly-cited patents. Moreover, VC-backed firms are disproportionately likely to have more original patents, more general patents, and patents more closely related to fundamental science. This 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, we find that 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, is 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 these periods are associated with *particularly* low levels and quality of innovation.

Third, we find that our innovation results, like the deal volume results, are driven by startups financed by venture groups who specialize in early-stage investment. In some specifications, there are few differences in the volume of innovation across the business cycle for startups backed by late-stage investors. 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.

Fourth, we find that the shift in innovation we measure during recessions stems from both the types of firms receiving VC financing during recessions and a change in the nature of innovation within VC-backed firms over the course of the business cycle. Specifically, our results appear to be driven by startups that raised their most recent round either during the recession or many months before it started. Startups that raised their most recent VC round during the six months before the recession started (i.e., during the boom period) experience no relative decline in innovation quality.

Why would VC-backed investment and innovation decline during recessions? The potential mechanisms can broadly be grouped into those related to shifts in investment opportunities, or difficulty evaluating them (Howell 2020), shifts in human capital of entrepreneurs seeking capital (Rampini 2004), and frictions or constraints in the supply of venture capital financing innovation during downturns (Townsend 2015; Nanda and Rhodes-Kropf 2017).

All of these forces are likely at play, to a greater or lesser extent, in recessions. That said, the concentration of our investment and innovation results within venture groups focused on the early-stage investing (and the lack of correlation between affected public market sectors and affected VC sectors that we document in the COVID-19 crisis) suggests an important potential friction facing the supply of early-stage capital itself. For example, Townsend (2015) shows that venture capitalists with heavy exposure to information technology after the dot com collapse of the early 2000s were more likely to terminate funding for non-IT companies (e.g., biotechnology), suggesting that their inability to raise capital after the bust led to termination of companies with positive net present value. Even venture groups that have abundant capital may anticipate future liquidity constraints and act accordingly. This effect 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 otherwise healthy startups may not receive financing even if the VC firm itself is not constrained, due to a forecast of limited future funding from other venture firms.

This 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 innovation should be counter-cyclical because creative destruction occurs in recessions. This hypothesis, articulated by Schumpeter (1939), has been developed in Caballero and Hammour (1994), Aghion et al. (2012), and Barlevy (2007), among others. Babina (2020) provides microeconomic evidence, showing that firm distress leads employees to depart to start new firms.

On the other hand, there is substantial empirical evidence that innovation overall is pro-cyclical, including Griliches (1984) and Comin and Gertler (2006). At the level of the individual inventor, Bernstein, McQuade, and Townsend (2020) show how financial distress deters risky innovation. At the firm level, Fabrizio and Tsolmon (2014) argue that pro-cyclical innovation reflects incentives to shift innovation to booms, in order to capture high-potential profits before imitators can compete away rents. Manso, Balsmeier, and Fleming (2019) use data on large, 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. Our results complement the existing findings on large firms and individual inventors. We demonstrate that during recessions, there is a shift away from high-quality innovation among VC-backed startups, apparently because of shifts in the innovation that VC is 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 (Kortum and Lerner 2000; Puri and Zarutskie 2012; Gornall and Strebulaev 2015). 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, in fact deal activity is 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.

Our findings contribute 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). We also contribute to the broader 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). More generally, our work points to untangling potential explanations for extremely pro-cyclical early-stage VC investments as an important area of future inquiry.

2 Data

We seek to characterize the venture market activity in the short-run around the COVID-19 crisis, as well as market activity and innovative behavior over a much longer time span. To do this, we use several datasets.

2.1 COVID-19 analysis

2.1.1 Sources

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 the advantage of 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.

2.1.2 Key variables

We are interested in whether the stock market and the VC market responded similarly to the crisis, specifically at the sector level. We begin by identifying the hardest-hit sectors among public companies whose stock is traded on the major U.S. exchanges. We gathered 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. We aggregated 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, GICS ("Global Industry Classification Standard") assigns firms to sectors that are designed to capture present-day investment-driven industries. We use the 2018 sector assignment, which is the most recent available.[5] We focus on the 6-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 Figure A-1 in the appendix. 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.

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

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 Figure A-1 in the appendix into four quartiles ranging from most to least affected. Then we assigned 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."[6]

2.2 Historical recession analysis

2.2.1 Sources

To analyze how VC deal activity responded to past recessions, we use data from the Refinitiv VentureXpert database. VentureXpert, along with Dow Jones' VentureSource (formerly VentureOne), are the two primary venture capital databases. We use VentureXpert because it starts earlier (1962 vs. 1994) and has been found to be more comprehensive in terms of investment coverage, which is important for our purposes.[7] VentureXpert records detailed information about the dates of venture financing rounds, the VC firms and companies involved, the amounts invested by each party, and the ultimate company outcome.

To analyze how VC-backed innovation responded to past recessions, we combine the data from VentureXpert with patent data from the U.S. Patent and Trademark Office (USPTO). The USPTO data cover all U.S. utility patents issued between January 1,

[6] 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.

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

1976 and December 31, 2017, as well all citations in these patents. The merged dataset consists of 5.42 million utility patents that were assigned to firms. For each patent, we can observe the date it was applied for, the firm it was assigned to, its primary 3-digit USPC field classification, the backward citations it made to other patents, and the forward citations other patents made to it.[8]

2.2.2 Key variables

VC affiliated patent. We wish to examine innovation by 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 affiliated with a VC if the firm it was assigned to was financed by a VC and its application date is 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 examine the robustness of the results to an alternative definition, which considers a patent to be affiliated with a VC if its application date is in the first 4 years after its assignee's first VC financing round. This period corresponds to the average period that 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 we construct is simply the number of forward (subsequent) citations a patent received from other patents granted through 2017. Forward citations are widely viewed as a good proxy for the quality of a patent. We define a top cited patent to be one that is in either the top 10% or top 1% among all patents applied for in the same month.

Top originality score patent. Patent originality is a measure of how dispersed a

[8]The U.S. switched to classifying patents using the Combined Patent Classification scheme in 2013. The patent class data come from the U.S. Master Classification File (MCF). The USPTO kept classifying patents by USPC, even after the switch to CPC, at least through early 2020. These data are compiled at https://bulkdata.uspto.gov/data/patent/classification/.

patent's backward citations are across different fields, where fields are based on patents' primary 3-digit USPC classifications (as in Hall, Jaffe, and Trajtenberg (2001) and related publications). 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 U.S. patent class and (b) the total number of such citations. We define a top originality score patent to be one that is in either the top 10% or top 1% among all patents applied for in the same month.

Top generality score patent. Patent generality is a measure of how dispersed a patent's forward citations are across different fields. A patent is considered more general if it influences subsequent innovations in many different areas. This measure is defined analogously to originality. We define a top generality score patent to be one that is in either the top 10% or 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 either the top 10% or top 1% among all patents applied for in the same month.

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 either the top 10% or top 1% among all patents applied for in the same month.

3 An Early Look at the COVID-19 Recession

We begin by taking a first look at the COVID-19 crisis. Here, given the very recent timing, we can only look at the changes in the volume of financing, not the consequences of these changes on innovation.

In Figure 1, 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 October 28, 2019 and May 2, 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 reported.[9]

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 later-stage deals. Second, amounts are only reported for a selected fraction of deals, leading us to be concerned about potential biases.

The top left graph of Figure 1 shows that early-stage VC deals declined from an average of 112.3 deals per week before the crisis to 69.7 deals per week on average in the two months after the crisis, representing a decline of 38%. 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

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

graphs, we consider later-stage VC deals. Perhaps surprisingly, any effect of the crisis for later-stage deals is substantially muted.[10]

If the large decline reflects demand trends, either poor near-term cash flow outlooks or the difficulty of assessing product-market fit, we would expect that the sectors worst hit in the public markets would also experience the greatest decline in VC activity. In Figure 2, we divide the industries into quartiles by the mean raw market returns, as described in Section 2.1. 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. Note that because we include later-stage deals, which experience a smaller decline, the average decline is less than the average early-stage decline. Surprisingly, the green bars indicate a broad-based decline in venture activity across both the sectors more and less affected by the public market.

We reach similar conclusions in an industry-by-industry comparison with Pitchbook data. We match each 6-digit GICS sector to a 2-digit Pitchbook sector.[11] The left graph of Figure A-2 in the Appendix plots the stock market returns, again as described in Section 2.1, categorized by 2-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 is true at the 4-digit Pitchbook level as well. With 139 4-digit industries, we find a correlation of .03 between the change in stock market returns and the change in early VC deals. This

[10] In Figure A-3 of the appendix, we show the decline using data from CB Insights, similarly for October 1 2019-May 1, 2020. Using these data, early-stage deals decline from an average of 50 per week pre-COVID-19 to 37 per week in the post-period, a decline of 26%.

[11] 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.

exercise suggests that VC sensitivity to the crisis was not only driven by demand changes for startups' goods and services. Rather, this result points to financing risk as a potential explanation for the downturn.

This explanation is motivated by the fact that many obvious competing mechanisms appear unlikely to be at play during the immediate phases of the COVID-19 downturn. In particular, we have observed a sharp demand-driven economic crisis without several confounding factors present during historical recessions. First, the COVID-19 crisis has not been associated with an immediate liquidity crunch or significant decline in the supply of capital. 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." Moreover, the COVID-19 crisis occurred at a time when private markets were extremely healthy. In January 2020, venture capital funds had a record amount of committed but uninvested capital, or "dry powder," totaling $276 billion.[12] Therefore, the capital supply rationale for declining investment should not be at play.

Second, unlike earlier recessions, the COVID-19 crisis is arguably exogenous to the supply of innovation and entrepreneurs, particularly in the short term. This is because it originated as a pandemic, rather than a shock to markets. Within a month of the onset of the crisis, it is implausible that the supply of entrepreneurial firms at hazard of raising VC shifted suddenly, given that launching a new firm and conducting the fundraising process is a process that does not occur within a time-frame of a few weeks. Yet as Baker et al. (2020) show, COVID-19 had an immediate and massive impact on the stock market. More generally, Ludvigson, Ma, and Ng (2020) find that COVID-19 is unique among catastrophic events over the past four decades, in that it disrupted labor market activities rather than destroying capital, is national rather than local, and has a duration of months rather than lasting only for days.

[12] See https://www.wsj.com/articles/venture-firms-dry-powder-reaches-record-level-11578571201.

4 Historical Analysis of Venture Capital, Recessions, and Innovation

We begin by showing the patterns of venture financing displayed during the COVID crisis are consistent, at least at a broad level, with those seen in earlier recessions. We then shift our focus to the impact of recessions on venture-backed innovation. We show that venture-backed firms are generally more innovative than non-venture-backed firms, but this "venture advantage" varies pro-cyclically over the business cycle. Finally, we seek to better understand the drivers of these fluctuations.

4.1 The impact of earlier recessions on venture investment

We begin by asking whether the striking patterns seen in the COVID-19 recession—a broad retreat from early-stage investment—were repeated in earlier recessions. As delineated in Section 3, the recent downturn had certain idiosyncratic aspects that differentiate it from earlier downturns. To examine this, we look at the number and dollar size of venture investments, with an eye to how VC investment activity changed during recessions. We use, as elsewhere in Section 4, monthly data from Refinitiv, and define recessions as the months during the peak to trough identified in NBER business cycle data (https://www.nber.org/cycles.html). Figure 3 plots the number of venture deals, the S&P 500 index, and NBER recessions.

In Panel A of Table 1, the dependent variables are log dollar amount (columns (1) and (2)) and total number (columns (4) and (5)) of early- and late-stage VC deals in the month. Columns (3) and (6) look at the difference between early- and later-stage deals. Panel B similarly looks at the logged and unlogged amount of investment per deal, following a similar structure.

The table suggests that the patterns seen in the COVID-19 recession reflect those in earlier downturns. Investments in early-stage transactions fall off sharply in recessions, far more so than later-stage ones. These patterns hold whether we look at the dollar volume or number of deals, or transaction size. Specifically, in recessions the amount of early-stage investment falls by 39% (Panel A column 1), the number of deals falls by 33% (Panel A column 4), and the amount per deal falls by at least 25% (Panel B columns 1). Meanwhile, there is no measurable relationship between recessions and later-stage activity (columns 2 and 5 in both panels). In all cases, the difference between early and late deals is statistically significant (columns 3 and 6 in both panels).

4.2 The relative innovativeness of VC-backed firms

We next seek to characterize the relative innovativeness of venture-backed firms by comparing their patents to other awards. Table 2 presents, for all awards made between 1976 and 2017, the share of all patents and VC-backed patents that fell into each category defined in Section 2.2.2.

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 citations,[13] 4.7% of the venture-backed firms were. Put another way, VC-backed patents were 4.6 times overrepresented among these top-cited patents. Results using other metrics, including the top 1% in generality, originality, and academic citations, are similar. In unreported regressions, we explore other metrics, such as patents in the 0.1% and 0.01% of citations, as well as calculated in other ways (e.g., relative all patents awarded in the same year). The results are robust.

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

4.3 The temporal pattern of innovativeness

Next, we examine how these patterns change over time. In particular, we seek to understand how the relatively greater innovativeness of VC-backed firms varies over the business cycle. Figure 4 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 in the next six tables. In each case, we report regressions where each observation is a single patent. In Table 3, the dependent variable is an indicator variable equal to one if the patent is venture-backed. In Tables 4 through 8, the dependent variable is an indicator equal to one if the patent is venture-backed and is also in the top 10% or 1% of patents from the same month, using the metrics described in Section 2.2.2. In each table, the independent variables include controls for the U.S. patent class and the geography of the inventor (foreign inventors may mechanically have fewer citations, as subsequent patents may cite their original overseas filing instead).

The key independent variables of interest to us are (1) The log of the dollar volume of aggregate VC investment in the month the patent was applied for and (2) an indicator equal to one if the month the patent was applied for was during a recession, defined as a month between the peak and trough as identified by the National Bureau of Economic Research. Standard errors are clustered by month.

These tables tell a consistent story. First, Table 3 shows that the share of patents associated with venture capital-backed firms falls during recessions. Moreover, this remains true even after controlling for the reduced VC investment activity associated with recessionary periods.

The production of high-impact patents follows a similar pattern. The results vary with the specification, but in general the production of high-quality patents is greatest during boom periods, and falls sharply during recessions. (The only exceptions are the analyses of the 10% patents using the originality and the top scientific journals measures.)

Many of the results are robust to looking at different cut-off points, such as 0.1% and 0.01% patents, as well as different ways to calculate the most influential patents (e.g., by year or absolutely). Several robustness analyses using the patent citation measures are reported in Table A-1 in the appendix.

We can assess the magnitude of the coefficients by examining regression (3) in Table 4. A one standard deviation increase in the log volume of venture capital financing in the month (2.19, when evaluated across the 526 months in the sample) raises the probability that a patent is simultaneously venture-backed and in the top 10% of citations by 0.16%. This is economically meaningful relative to the baseline probability of 0.55% (=1.9% * 29%, both from Table 2), representing a 30% increase. If the patent is filed during a recession, the probability drops by nearly 0.1%, representing a 17% decline from the baseline.

The analyses in Section 3 and 4.1 suggested the dynamics of early- and later-stage investment during recessions was quite different: early-stage investors responded more sharply to shifts in economic conditions. Thus, it is natural to wonder whether the consequences for innovation of being backed by early- and late-stage investors are different.

We analyze this question in Table 9. We identify early- and late-stage investors by the share of their previous investments that were in companies defined by VentureXpert as "seed" and "early-stage." We characterize early-stage investors as those whose share is above the median, and vice versa.

The table has separate panels for patents and citations, originality and generality, and closeness to science. Across each of these measures, we see the effect of recessions is more negative for early- than late-stage investors at the one-percent confidence level. Firms backed by early-stage investors undergo a sharper reduction of patenting during recessions, especially for important awards.

The magnitude of these changes can be illustrated by examining regressions (7) and (8) in Panel A (corresponding to the citation analysis whose coefficients were discussed above). A patent applied for during a recession is 0.08% less likely to be a top 10% patent if the firm is backed by an early-stage investor (again, economically meaningful relative to the baseline). If backed by a later-stage investor, the probability of being in the top 10% insignificantly increases. Table A-2 in the Appendix shows the results with the top 1% of patents: while less consistently significant, the results are of similar direction and economic magnitude.

4.4 Understanding the mechanisms

A natural follow-on question relates to the mechanisms at work here. What can explain this decline of innovative output by venture-backed firms during recessions, particularly the shrinking share of high-impact patents?

4.4.1 Intensive vs. extensive margin

One possibility is that venture-backed patents account for a smaller share of top-cited patents during recessions simply because venture-backed patents account for a smaller share of all patents during these periods—as shown in Table 3. To test whether that is the case, in Table 10 we first repeat the analysis of Table 4 but now limiting the sample only to patents of venture-backed firms. In the odd-numbered columns, we find that venture-backed patents that are applied for during recessions are less likely to be top-cited than venture-backed patents applied for during booms. Thus, our baseline results in Table 3 do not appear to be driven entirely by a general decline in venture-backed patenting. If that were the case, then conditional on a patent being venture-backed, it would be no less likely to be a top-cited patent based on when it was applied for.

In the even-numbered columns of Table 10, we explore whether the decline documented in the odd columns is driven by changes in the innovativeness of existing firms (i.e., the intensive margin) or by changes in types of firms backed by venture capitalists (i.e., the extensive margin). We do this by including assignee (i.e., firm) fixed effects in the regressions. As can be seen, once assignee fixed effects are included, the coefficient on the recession term drops sharply, and frequently become statistically insignificant. These results suggest that it is extensive margin that is most important. In other words, venture groups fund less innovative firms during recessions.

4.4.2 Supply of capital vs. demand

We can also use fundraising timing to test whether demand for goods and services or capital supply is the most salient mechanism. 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. Now suppose instead that the mechanism is that the supply of VC financing is lower, higher-priced, and perhaps less oriented towards risky inventions during recessions. Then we expect that those startups with the good timing to have raised immediately before the recession, and thus have a relatively plentiful cash "runway," will be more insulated from the negative effects of recessions on patent quality.

Table 11 shows that timing of fundraising matters greatly to our findings. The dependent variable is as defined in Table 4 but with an additional criterion based on when the VC-backed assignee raised its most recent VC financing round. In columns 1 and 3, the dependent variable is an indicator for being a top cited patent with VC affiliation where the most recent round occurred in the six months before the beginning of the recession.

These startups raised during the "peak" of the boom, likely at relatively more favorable valuations, and have more liquidity during the recession. We find that the coefficient is positive for top 10% patents (column 1) or insignificant for top 1% patents (column 3). Startups that raised in the peak are, if anything, producing higher quality patents than their peers during recessions. In columns 2 and 4, the dependent variable is an indicator for being a top cited patent with VC affiliation where the most recent round occurred either during the recession or prior to six months before the first month of the recession. These startups likely have less runway or had to raise at less favorable valuations. The effects are similar to our main findings in Table 4, indicating that those results are driven by firms that did not raise funding during the peak. In sum, this exercise supports the capital supply story.

4.5 Robustness Tests

Appendix Table A-3 demonstrates that the lower quality of VC patents in recessions does not spuriously reflect changes to firm patenting behavior more generally. It also clarifies that the results do not somehow reflect a broader relationship between VC funding and patent quality, nor one between recessions and patent quality. In columns 1 and 4, the dependent variable is an indicator that the patent is a top-cited one. The coefficient of interest is on the interaction between the month being in a recession and the patent being VC-affiliated. We observe in column 4 a coefficient of -0.6%, which implies that relative to non-recession periods and relative to non-VC patents, being a VC patent in a recession period is associated with a 60% lower probability of being a top cited patent. (Of course, the mean of the dependent variable is 1% by construction.) The remaining columns show that this effect is magnified for early deals, both defined at the investor level as in Table 9 (columns 2,5), as well as at the deal level (columns 3,6). The deal-level indicator takes a value of one if the deal is designated by Refinitiv as Early-Stage.

There may be concern that since NBER recessions are most relevant to the U.S. economy, and the vast majority of VC deals in the sample are for U.S. firms, the inclusion of foreign patents somehow magnifies the relationship between VC funding and patent quality. In Appendix Table A-4, we show that our results are instead larger when we exclude foreign patents. For example, in column 4, we find that recessions are associated with a -0.05% decline in the probability of being a top 1% cited patent with VC affiliation, almost double the baseline effect.

5 Final Thoughts

Motivated by the consequences of the COVID-19 recession on the venture market, we explore whether the volume and quality of VC-backed innovation benefits or suffers during downturns. A preliminary look at the weeks following the COVID-19 crisis suggests that there has a sharp decline in the volume of venture financing. Rather than being concentrated in particular sectors, the downturn occurred across a wide variety of industries but was concentrated in early-stage investments. Looking over the past 40 years, we see that this pattern occurred in earlier recessions as well.

Turning to the relative innovativeness of VC-backed firms, we find consistent evidence that venture-backed firms have more influential and fundamental patents. But the volume of venture-backed patents in general, and especially the most cited and those with the closest connections to academic research, are highly pro-cyclical. Even after controlling for the changing level of VC activity over time, the impact of recessions is highly adverse to venture-backed innovation, particularly for firms backed by early-stage investors.

These results suggest a variety of open questions about the implications of these patterns for social and private optimality. It might be anticipated that drop-off of venture-driven innovation associated with recessions might be socially detrimental, especially given the overrepresentation of VC-backed awards among the most influential patents. (To the extent that some of the research during booms is more duplicative, the effect could be muted.) The private optimality of these cyclic patterns is more complex. Whatever the social consequences, it may well be privately optimal for firms to cut back on ground-breaking work in periods where risk and liquidity are restricted, particularly if this work will take longer to reach the marketplace. These issues deserve careful scrutiny.

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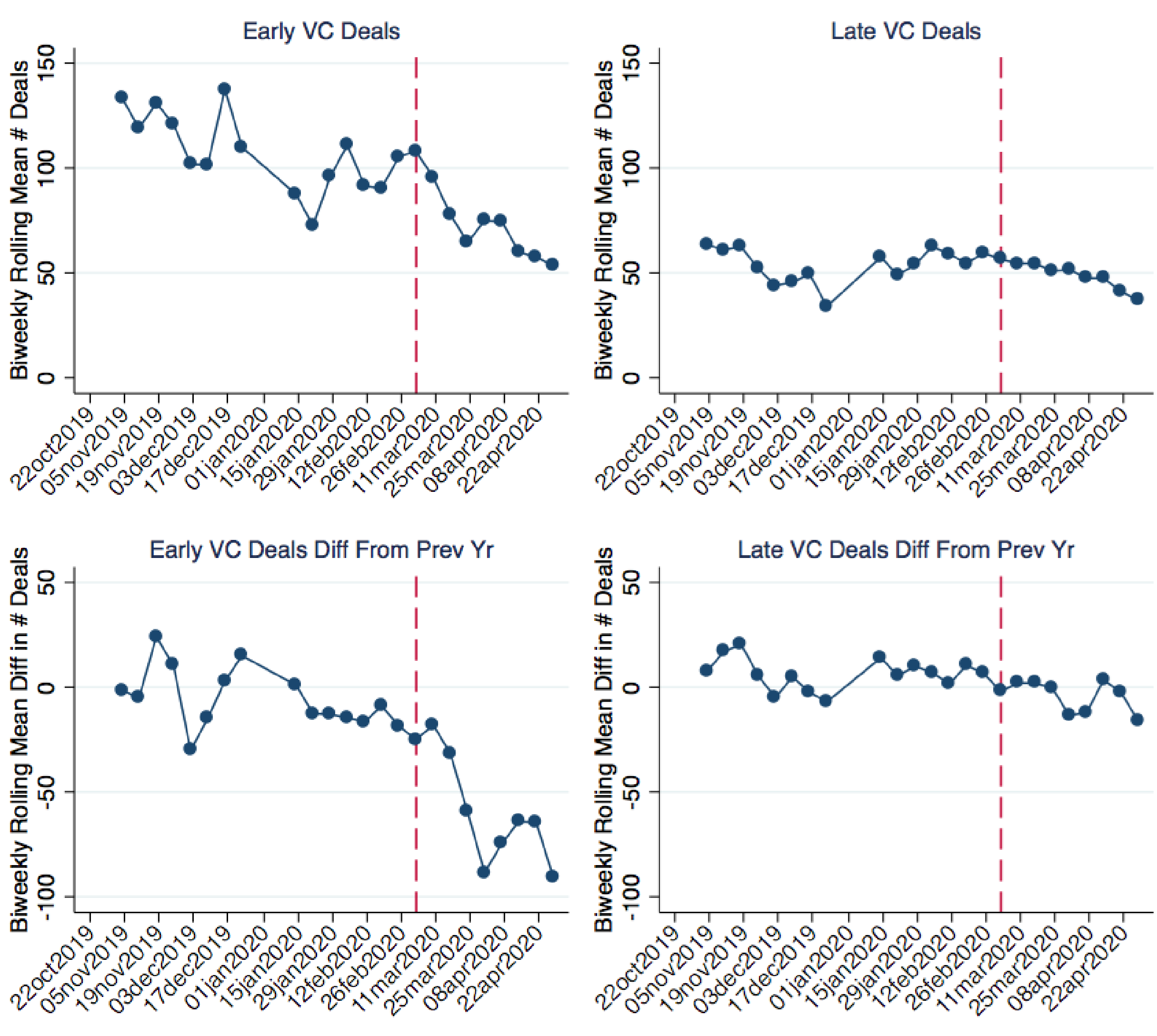
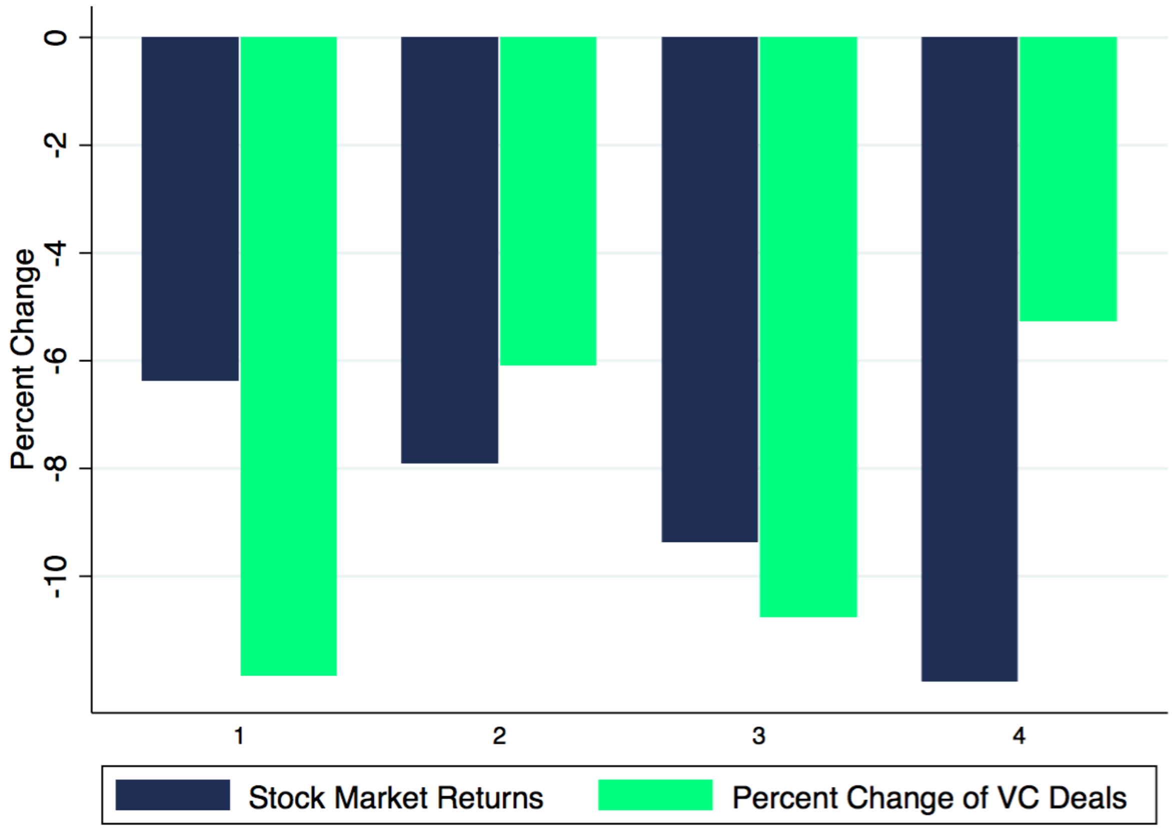
Figure 1: US VC Deals Around COVID-19 Crisis by Stage (Pitchbook)



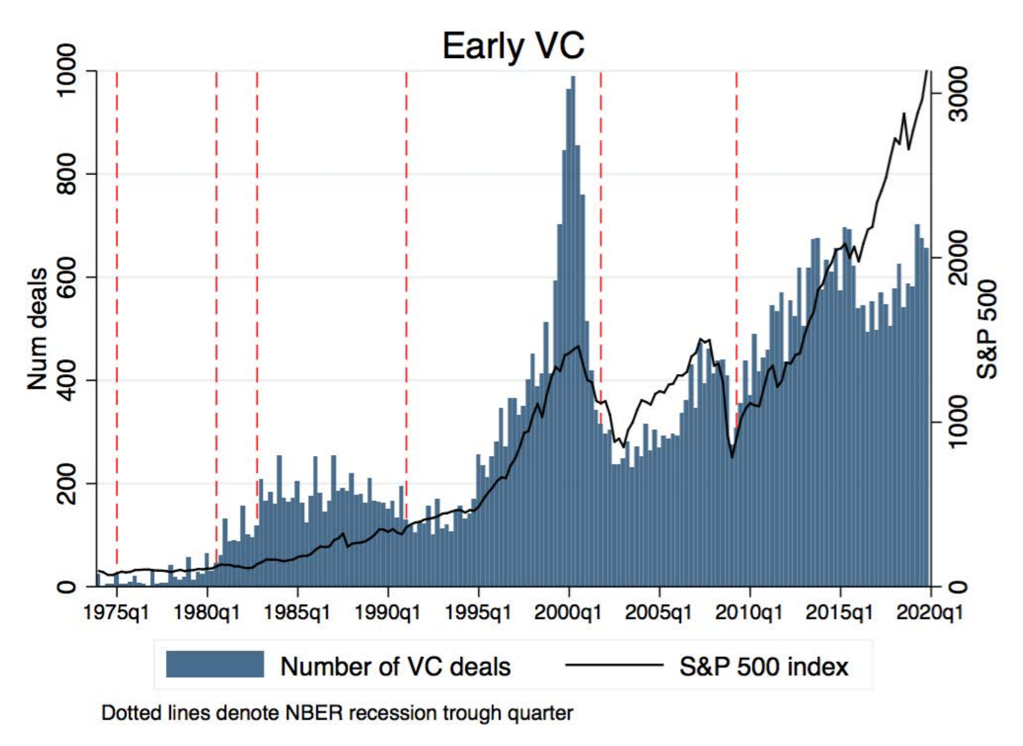
These figures show the number of US VC deals by investment stage using data from Pitchbook. Frequency is weekly, and the first day of the week is shown on the x-axis. Each point represents a biweekly rolling mean, which is the mean taken over this week and the previous week. The red line at the first 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.

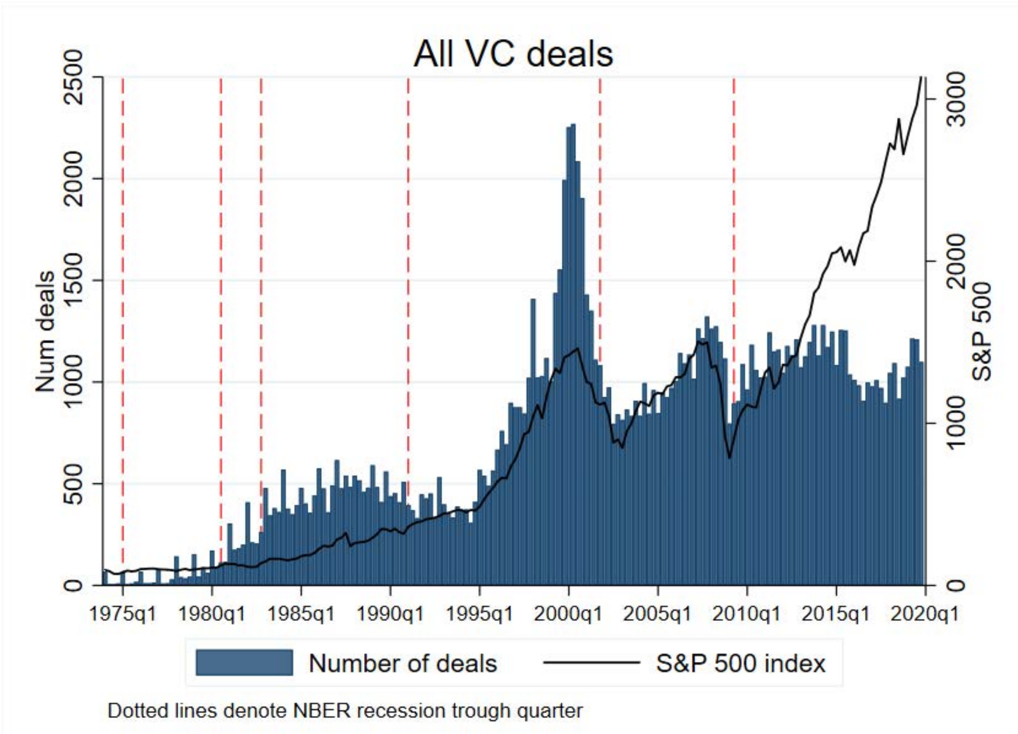
Figure 2: Comparison of Change in VC and Stock Market Returns by Quartile of Stock Market Returns during COVID-19 Crisis



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 6-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.

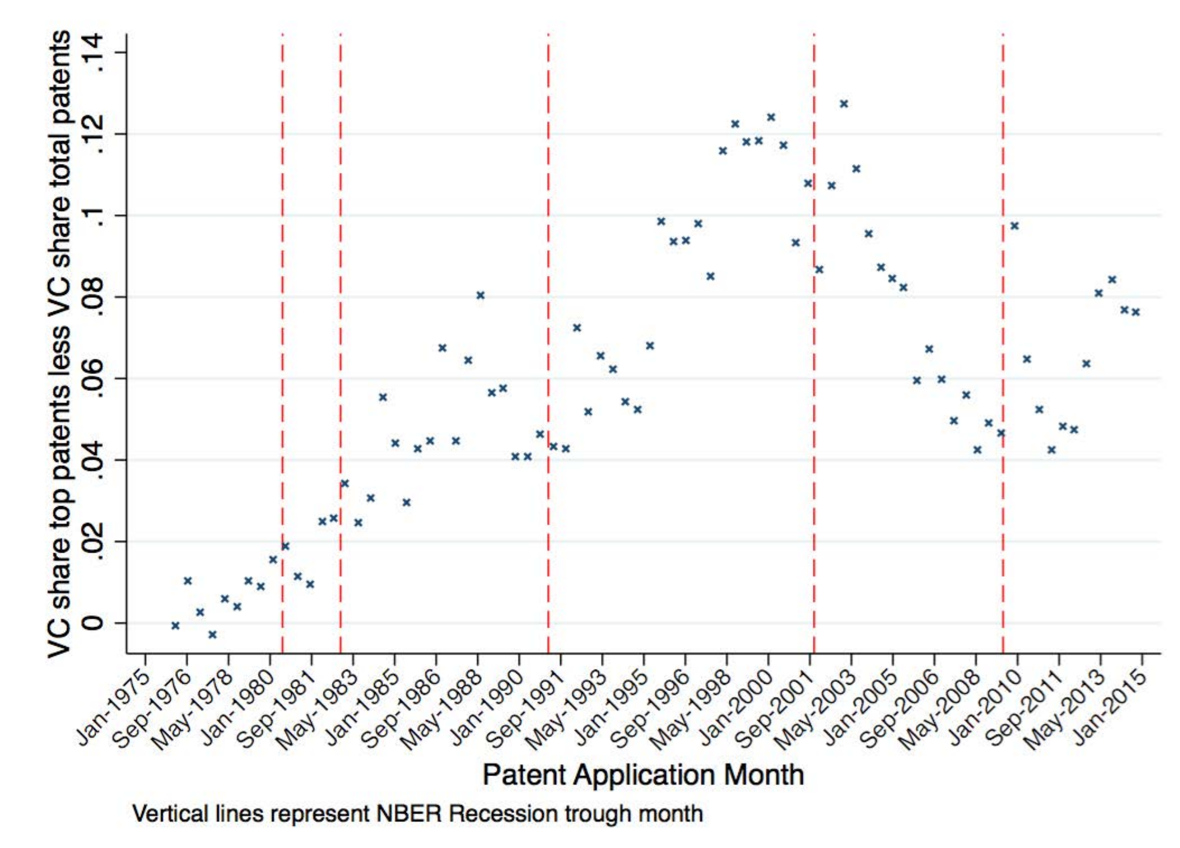
Figure 3: VC Investment and Market Cycles





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

Figure 4: 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, 2014 (subsequent data on citations exhibit strong truncation bias). Vertical lines represent the trough month of NBER recessions. Sources: USPTO, VentureXpert.

Table 1: 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 1990 and March 2020. Both panels use monthly data and robust standard errors. 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 Panel 1, the dependent variables are the log of the total dollar amount of early and late VC deals in the month (Columns (1) & (2)), the log of the total amount of early VC deals in the month minus the log total amount of late VC deals in the month (Column (3)), the number of early and late VC deals in the month (Columns (4) & (5)), and the number of early VC deals in the month minus the number of late VC deals in the month (Column (6)). The dependent variables in Panel 2 are the log of the dollar amount per transaction in early and late VC deals (Columns (1) & (2)) and the nominal dollar amount per transaction in early and late VC deals (Columns (4) & (5)). The dependent variable in Column (3) is the difference in the log average amount in early and late VC deals. In Column (6), the dependent variable is the difference in the average amount in early and late VC deals. At the bottom of both panels are the means of the dependent variables during non-recession periods. All amounts are in real 2019 dollars.

Panel A: Log Total Amount and Total Number of VC Deals

	Log Amount of VC			Number of VC Deals		
	Early (1)	Late (2)	Early - Late (3)	Early (4)	Late (5)	Early - Late (6)
$\mathbb{1}$(Recession)	-0.396***	-0.177	-0.218**	-33.027***	22.110	-56.348***
	(0.146)	(0.187)	(0.093)	(8.285)	(14.677)	(6.978)
R-Squared	0.015	0.003	0.013	0.018	0.006	0.119
Observations	364	364	364	364	364	364
Non Recession Mean	13.493	14.452	-0.959	139.399	172.045	-32.647

Panel B: Amount and Log Amount per VC Deal

	Log Amount per Deal			Amount per Deal (000s)		
	Early (1)	Late (2)	Early - Late (3)	Early (4)	Late (5)	Early - Late (6)
$\mathbb{1}$(Recession)	-0.255***	-0.036	-0.218**	-558.141***	-88.739	-537.212*
	(0.098)	(0.137)	(0.094)	(97.209)	(384.612)	(302.372)
R-Squared	0.009	0.000	0.013	0.015	0.000	0.249
Observations	364	364	364	364	364	364
Non Recession Mean	7.002	7.961	-0.959	1502.723	3577.398	-2074.674

Table 2: Summary Statistics

VC affiliated 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. *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 affiliated)	0.01865		
$\mathbb{1}$(Top 10% citations)	0.11151	0.29412	2.63758
$\mathbb{1}$(Top 1% citations)	0.01026	0.04681	4.56159
$\mathbb{1}$(Top 10% originality)	0.09303	0.16338	1.75616
$\mathbb{1}$(Top 1% originality)	0.01106	0.02247	2.03088
$\mathbb{1}$(Top 10% generality)	0.10323	0.19369	1.87624
$\mathbb{1}$(Top 1% generality)	0.01042	0.02733	2.62142
$\mathbb{1}$(Top 10% closeness to sci.)	0.10901	0.27976	2.56623
$\mathbb{1}$(Top 1% closeness to sci.)	0.01030	0.04048	3.92893
$\mathbb{1}$(Top 10% closeness to quality sci.)	0.07739	0.21131	2.73049
$\mathbb{1}$(Top 1% closeness to quality sci.)	0.00974	0.03773	3.87509
Observations	5,235,206	97,635	

Table 3: VC affiliated patents over the business cycle

Observations are U.S. utility patents awarded between between January 1, 1976 and December 31, 2017. *VC affiliated 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. *Foreign patent FE* is an indicator variable equal to one if any of the patent assignees were not based in the U.S. *Class FE* represent class fixed effects based on the patents primary, 3-digit USPC class. Standard errors are clustered by application month. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	$\mathbb{1}$(VC affiliated patent)		
	(1)	(2)	(3)
$\mathbb{1}$(Recession)	-0.00207***		-0.00160***
	(0.00066)		(0.00042)
Log VC investment		0.00279***	0.00278***
		(0.00010)	(0.00010)
Patent Class FE	Yes	Yes	Yes
Foreign Patent FE	Yes	Yes	Yes
R-Squared	0.028	0.029	0.029
Observations	5,227,372	5,227,372	5,227,372

Table 4: Top cited patents with VC affiliation

Observations are U.S. utility patents awarded between between January 1, 1976 and December 31, 2017. *Top cited patent with VC affiliation* is an indicator variable equal to one if one of the patent assignees is a VC-backed firm as of the patent application date and is in the top 10% (columns 1–3), or 1% (columns 4–6) of forward citations among patents from the same application month cohort. 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. *Log VC investment* is the log of aggregate VC investment in the 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. *Foreign patent FE* is an indicator variable equal to one if any of the patent assignees were not based in the U.S. *Class FE* represent class fixed effects based on the patents primary, 3-digit USPC class. Standard errors are clustered by application month. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	$\mathbb{1}$(Top cited patent with VC affiliation)					
	Top 10%			Top 1%		
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$(Recession)	-0.00106***		-0.00094***	-0.00027***		-0.00025***
	(0.00022)		(0.00018)	(0.00006)		(0.00005)
Log VC investment		0.00076***	0.00075***		0.00010***	0.00009***
		(0.00003)	(0.00003)		(0.00001)	(0.00001)
Patent Class FE	Yes	Yes	Yes	Yes	Yes	Yes
Foreign Patent FE	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.014	0.014	0.014	0.005	0.005	0.005
Observations	5,227,372	5,227,372	5,227,372	5,227,372	5,227,372	5,227,372

Table 5: Top originality score patents with VC affiliation

Observations are U.S. utility patents awarded between between January 1, 1976 and December 31, 2017. *Top originality score patent with VC affiliation* is an indicator variable equal to one if one of the patent assignees is a VC-backed firm as of the patent application date and is in the top 10% (columns 1–3), or 1% (columns 4–6) of originality score among patents from the same application month cohort. 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. *Log VC investment* is the log of aggregate VC investment in the 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. *Foreign patent FE* is an indicator variable equal to one if any of the patent assignees were not based in the U.S. *Class FE* represent class fixed effects based on the patents primary, 3-digit USPC class. Standard errors are clustered by application month. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	$\mathbb{1}$(Top originality score patent with VC affiliation)					
	Top 10%			Top 1%		
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$(Recession)	-0.00017		-0.00009	-0.00009***		-0.00008**
	(0.00015)		(0.00011)	(0.00003)		(0.00003)
Log VC investment		0.00049***	0.00049***		0.00007***	0.00007***
		(0.00002)	(0.00002)		(0.00001)	(0.00001)
Patent Class FE	Yes	Yes	Yes	Yes	Yes	Yes
Foreign Patent FE	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.005	0.006	0.006	0.001	0.001	0.001
Observations	5,227,372	5,227,372	5,227,372	5,227,372	5,227,372	5,227,372

Table 6: Top generality score patents with VC affiliation

Observations are U.S. utility patents awarded between between January 1, 1976 and December 31, 2017. *Top generality score patent with VC affiliation* is an indicator variable equal to one if one of the patent assignees is a VC-backed firm as of the patent application date and is in the top 10% (columns 1–3), or 1% (columns 4–6) of generality score among patents from the same application month cohort. 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. *Log VC investment* is the log of aggregate VC investment in the 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. *Foreign patent FE* is an indicator variable equal to one if any of the patent assignees were not based in the U.S. *Class FE* represent class fixed effects based on the patents primary, 3-digit USPC class. Standard errors are clustered by application month. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	$\mathbb{1}$(Top generality score patent with VC affiliation)					
	Top 10%			Top 1%		
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$(Recession)	-0.00055***		-0.00045***	-0.00010**		-0.00009**
	(0.00014)		(0.00010)	(0.00004)		(0.00004)
Log VC investment		0.00060***	0.00060***		0.00011***	0.00011***
		(0.00002)	(0.00002)		(0.00001)	(0.00001)
Patent Class FE	Yes	Yes	Yes	Yes	Yes	Yes
Foreign Patent FE	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.006	0.006	0.006	0.001	0.001	0.001
Observations	5,227,372	5,227,372	5,227,372	5,227,372	5,227,372	5,227,372

Table 7: Top "closeness to science" patents with VC affiliation

Observations are U.S. utility patents awarded between between January 1, 1976 and December 31, 2017. *Top closeness to science patent with VC affiliation* is an indicator variable equal to one if one of the patent assignees is a VC-backed firm as of the patent application date and is in the top 10% (columns 1–3), or 1% (columns 4–6) of backward citations to academic research among patents from the same application month cohort. 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. *Log VC investment* is the log of aggregate VC investment in the 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. *Foreign patent FE* is an indicator variable equal to one if any of the patent assignees were not based in the U.S. *Class FE* represent class fixed effects based on the patents primary, 3-digit USPC class. Standard errors are clustered by application month. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	$\mathbb{1}$(Top closeness to science patent with VC affiliation)					
	Top 10%			Top 1%		
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$(Recession)	-0.00080***		-0.00063***	-0.00010**		-0.00008*
	(0.00023)		(0.00013)	(0.00005)		(0.00004)
Log VC investment		0.00098***	0.00097***		0.00013***	0.00013***
		(0.00004)	(0.00003)		(0.00001)	(0.00001)
Patent Class FE	Yes	Yes	Yes	Yes	Yes	Yes
Foreign Patent FE	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.018	0.019	0.019	0.009	0.009	0.009
Observations	5,227,372	5,227,372	5,227,372	5,227,372	5,227,372	5,227,372

Table 8: Top "closeness to quality science" patents with VC affiliation

Observations are U.S. utility patents awarded between between January 1, 1976 and December 31, 2017. *Top closeness to quality science patent with VC affiliation* is an indicator variable equal to one if one of the patent assignees is a VC-backed firm as of the patent application date and is in the top 10% (columns 1–3), or 1% (columns 4–6) of backward citations to academic research published in top journals among patents from the same application month cohort. 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. *Log VC investment* is the log of aggregate VC investment in the 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. *Foreign patent FE* is an indicator variable equal to one if any of the patent assignees were not based in the U.S. *Class FE* represent class fixed effects based on the patents primary, 3-digit USPC class. Standard errors are clustered by application month. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	$\mathbb{1}$(Top closeness to high quality science patent with VC affiliation)					
	Top 10%			Top 1%		
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$(Recession)	-0.00038		-0.00021	-0.00011***		-0.00009***
	(0.00026)		(0.00017)	(0.00004)		(0.00003)
Log VC investment		0.00098***	0.00098***		0.00010***	0.00010***
		(0.00004)	(0.00004)		(0.00001)	(0.00001)
Patent Class FE	Yes	Yes	Yes	Yes	Yes	Yes
Foreign Patent FE	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.019	0.019	0.019	0.012	0.012	0.012
Observations	5,227,372	5,227,372	5,227,372	5,227,372	5,227,372	5,227,372

Table 9: Heterogeneity by investor stage

Observations are U.S. utility patents awarded between between January 1, 1976 and December 31, 2017. Variables are as defined in Tables 3–8. Top refers to top 10% among patents from the same application month cohort. In the columns labeled Early VC (Late VC), the dependent variable is only equal to one if the venture groups the patent is affiliated with at the application date are early-stage (late-stage) venture groups. We consider a patent to be affiliated with the venture groups from its assignee's most recent financing round. To categorize affiliated venture groups as early-stage, we compute the percent of a syndicate's past portfolio companies that were early-stage at the time of investment. If this percentage is above the median, we consider the affiliated venture groups to be early-stage investors. Otherwise, we consider the affiliated groups to be late-stage investors. *P-value* reports the p-value associated with a test of the equality of the estimated coefficients on the *Recession* indicator across consecutive columns. It is calculated using a Seemingly Unrelated Regressions framework. Standard errors are clustered by application month. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Patents and citations

	𝟙(Patent with VC affiliation)				𝟙(Top cited patent with VC affiliation)			
	(1) Early VC	(2) Late VC	(3) Early VC	(4) Late VC	(5) Early VC	(6) Late VC	(7) Early VC	(8) Late VC
𝟙(Recession)	-0.00196***	0.00087*	-0.00186***	0.00118***	-0.00081***	-0.00008	-0.00079***	0.00001
	(0.00040)	(0.00052)	(0.00040)	(0.00032)	(0.00017)	(0.00014)	(0.00017)	(0.00010)
Log VC investment			0.00060***	0.00180***			0.00014***	0.00055***
			(0.00008)	(0.00007)			(0.00003)	(0.00003)
Patent Class FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Foreign Patent FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
P-value of difference	0.00		0.00		0.002		0.00	
R-Squared	0.013	0.014	0.013	0.015	0.006	0.007	0.006	0.007
Observations	5,227,372	5,227,372	5,227,372	5,227,372	5,227,372	5,227,372	5,227,372	5,227,372

Table 9: (Continued)

Panel B: Originality and generality

	𝟙(Top originality score patent with VC affiliation)				𝟙(Top generality score patent with VC affiliation)			
	(1) Early VC	(2) Late VC	(3) Early VC	(4) Late VC	(5) Early VC	(6) Late VC	(7) Early VC	(8) Late VC
𝟙(Recession)	-0.00039***	0.00029**	-0.00037***	0.00035***	-0.00044***	0.00005	-0.00041***	0.00010
	(0.00009)	(0.00013)	(0.00008)	(0.00009)	(0.00009)	(0.00011)	(0.00009)	(0.00008)
Log VC investment			0.00011***	0.00034***			0.00018***	0.00035***
			(0.00002)	(0.00002)			(0.00001)	(0.00002)
Patent Class FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Foreign Patent FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
P-value of difference	0.00		0.00		0.001		0.00	
R-Squared	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003
Observations	5,227,372	5,227,372	5,227,372	5,227,372	5,227,372	5,227,372	5,227,372	5,227,372

Table 9: (Continued)

Panel C: Closeness to science

	𝟙(Top closeness to sci. patent w/ VC affiliation)				𝟙(Top closeness to quality sci. patent w/ VC affiliation)			
	(1) Early VC	(2) Late VC	(3) Early VC	(4) Late VC	(5) Early VC	(6) Late VC	(7) Early VC	(8) Late VC
𝟙(Recession)	-0.00067***	-0.00003	-0.00064***	0.00008	-0.00040***	0.00002	-0.00035***	0.00013
	(0.00010)	(0.00020)	(0.00009)	(0.00013)	(0.00008)	(0.00020)	(0.00006)	(0.00015)
Log VC investment			0.00022***	0.00070***			0.00033***	0.00062***
			(0.00002)	(0.00003)			(0.00001)	(0.00003)
Patent Class FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Foreign Patent FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
P-value of difference	0.004		0.00		0.012		0.002	
R-Squared	0.008	0.010	0.008	0.011	0.008	0.011	0.008	0.011
Observations	5,227,372	5,227,372	5,227,372	5,227,372	5,227,372	5,227,372	5,227,372	5,227,372

Table 10: Intensive vs. extensive margin

Observations are U.S. utility patents awarded between between January 1, 1976 and December 31, 2017. The sample is limited to VC-affiliated patents. A patent assignee is defined as being VC-affiliated 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. Variables are as defined in Tables 3–8. *Assignee FE* represent patent assignee fixed effects. Standard errors are clustered by application month. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	𝟙(Top cited patent with VC affiliation)							
	Top 10%				Top 1%			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
𝟙(Recession)	-0.02855***	-0.01056*	-0.02817***	-0.01052*	-0.01022***	0.00003	-0.00998***	0.00004
	(0.00797)	(0.00567)	(0.00798)	(0.00582)	(0.00255)	(0.00199)	(0.00255)	(0.00198)
Log VC investment			-0.00651***	-0.01675***			-0.00431***	-0.00658***
			(0.00236)	(0.00295)			(0.00087)	(0.00128)
Assignee FE	No	Yes	No	Yes	No	Yes	No	Yes
Patent Class FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Foreign Patent FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.091	0.338	0.091	0.338	0.052	0.329	0.052	0.330
Observations	97,420	97,420	97,420	97,420	97,420	97,420	97,420	97,420

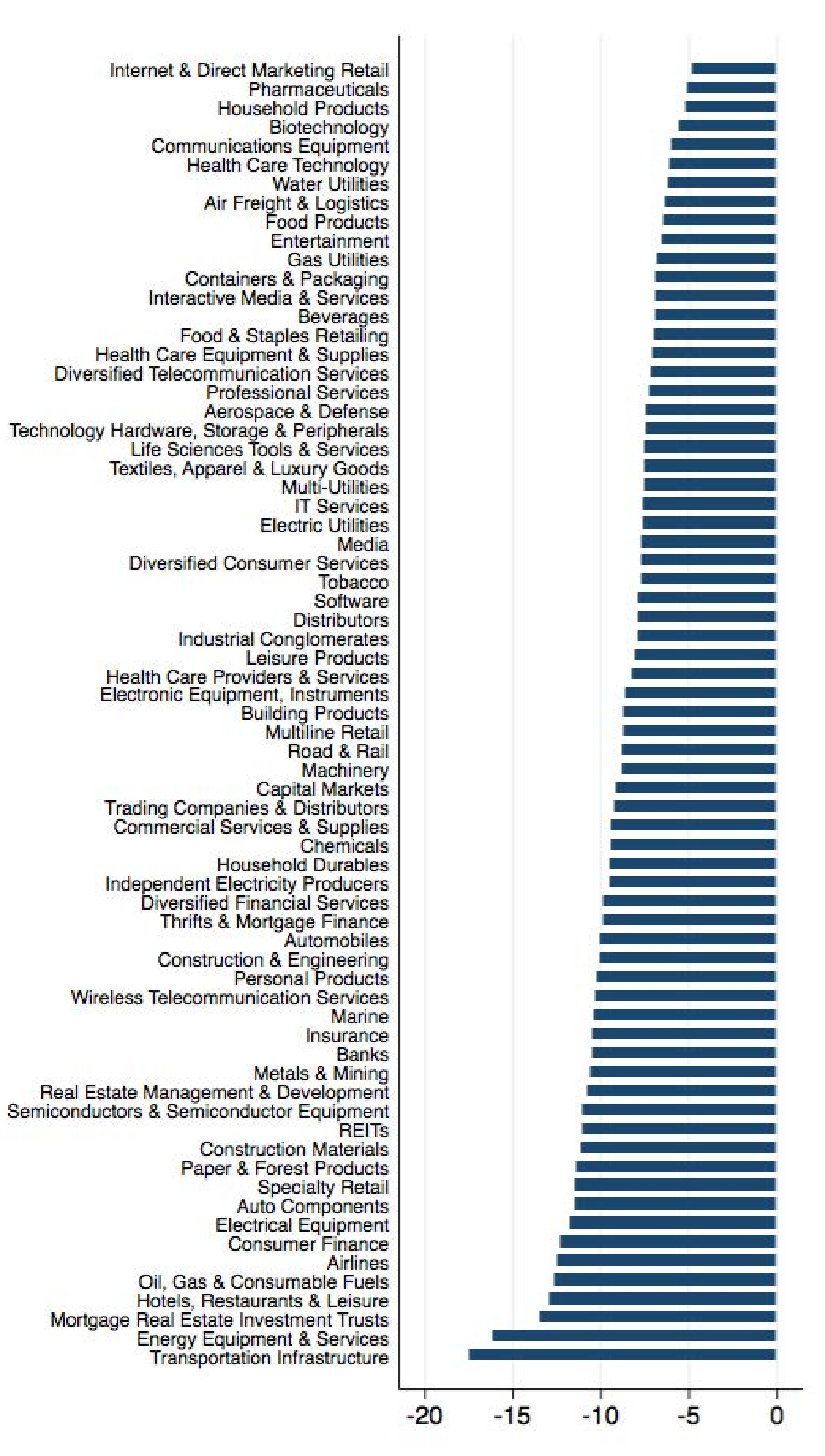
Table 11: VC Affiliated Patents by Fundraising Timing

Observations are U.S. utility patents awarded between between January 1, 1976 and December 31, 2017. The dependent variable is as defined in Table 4 but with with an additional restriction based on when the VC-backed assignee raised its most recent VC financing round. In columns 1 and 3, the dependent variable is an indicator for being a top cited patent with VC affiliation where the most recent round occurred in the six months before the first month of the recession. In columns 2 and 4, the dependent variable is an indicator for being a top cited patent with VC affiliation where the most recent round occurred either during the recession or prior to six months before the first month of the recession. Other variables are as defined in Tables 3–8. Standard errors are clustered by application month. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	$\mathbb{1}$(Top cited patent with VC affiliation)			
	Top 10%		Top 1%	
	(1) Raised in Peak	(2) Not Raised in Peak	(3) Raised in Peak	(4) Not Raised in Peak
$\mathbb{1}$(Recession)	0.00009**	-0.00094***	0.00001	-0.00025***
	(0.00004)	(0.00018)	(0.00001)	(0.00005)
Log VC investment	0.00008***	0.00075***	0.00000	0.00009***
	(0.00001)	(0.00003)	(0.00000)	(0.00001)
Patent Class FE	Yes	Yes	Yes	Yes
Foreign Patent FE	Yes	Yes	Yes	Yes
R-Squared	0.001	0.014	0.000	0.005
Observations	5,227,372	5,227,372	5,227,372	5,227,372

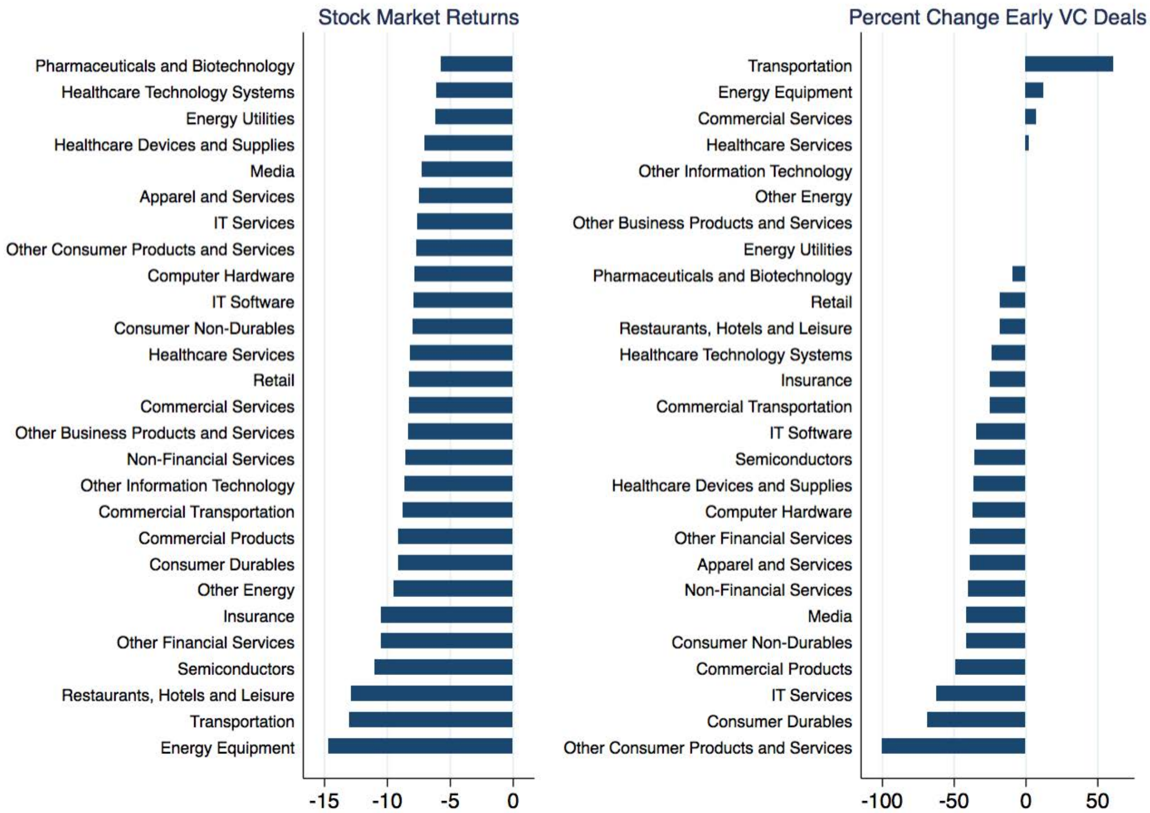
Appendix A Appendix

Figure A.1: Market Returns



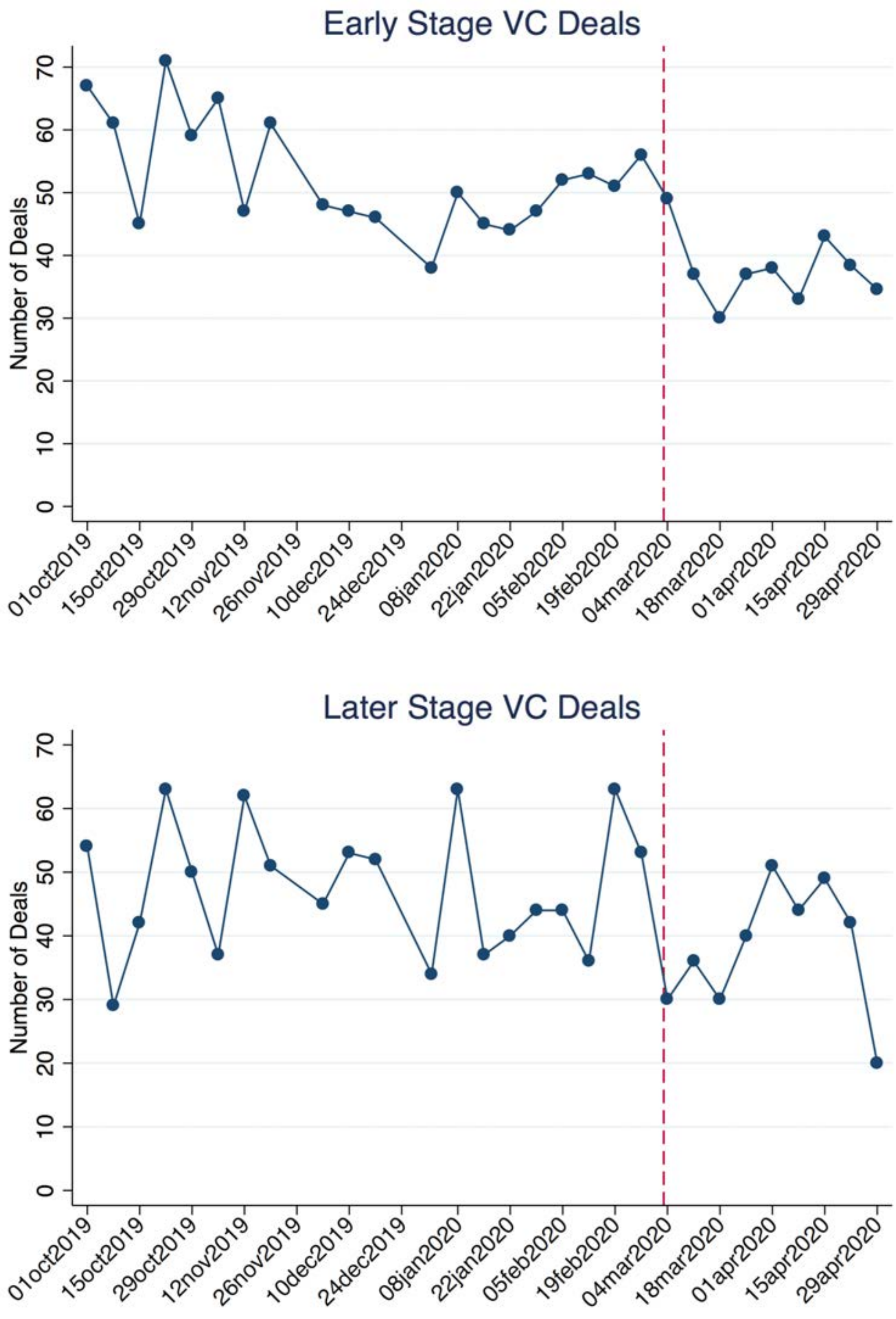
This figure shows the average daily value-weighted returns by 6-digit GICS sector across the five days in March 2020 with the largest drops in the S&P 500. Source: Datastream.

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 6-digit GICS sector mapped to 2-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.

Figure A.3: US VC Deals Around COVID-19 Crisis by Stage (CB Insights)



These figures show the number of US VC deals by investment stage using data from CB Insights. The frequency is weekly, and the first day of the week is shown on the x-axis. The red line at the first week of March 2020 represents the start (roughly) of the COVID-19 crisis in the U.S. Source: CB Insights.

Table A.1: Top cited patents with VC affiliation—Robustness

This table repeats the analysis of Table 4 but using different cutoffs for top patents. In Panel A, Top cited patent with VC affiliation is an indicator variable equal to one if one of the patent assignees is a VC-backed firm as of the patent application date and is in the top 0.1% (columns 1–3), or 0.01% (columns 4–6) of forward citations among patents from the same application month cohort. In Panel B, top patents are defined as those in the top 10% (columns 1–3), or 1% (columns 4–6) of forward citations among patents from the same application year cohort. Standard errors are clustered by application month. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Higher top cutoffs

	$\mathbb{1}$(Top cited patent with VC affiliation)					
	Top 0.1%			Top 0.01%		
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$(Recession)	-0.00007***		-0.00007***	-0.00001***		-0.00001***
	(0.00001)		(0.00001)	(0.00000)		(0.00000)
Log VC investment		0.00002***	0.00002***		0.00000	0.00000
		(0.00000)	(0.00000)		(0.00000)	(0.00000)
Patent Class FE	Yes	Yes	Yes	Yes	Yes	Yes
Foreign Patent FE	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.001	0.001	0.001	0.000	0.000	0.000
Observations	5,227,372	5,227,372	5,227,372	5,227,372	5,227,372	5,227,372

Table A.1: (Continued)

Panel B: Top cutoffs based on application year cohorts

	𝟙(Top cited patent with VC affiliation)					
	Top 10%			Top 1%		
	(1)	(2)	(3)	(4)	(5)	(6)
𝟙(Recession)	-0.00106***		-0.00094***	-0.00026***		-0.00024***
	(0.00023)		(0.00020)	(0.00005)		(0.00005)
Log VC investment		0.00075***	0.00075***		0.00010***	0.00010***
		(0.00003)	(0.00003)		(0.00001)	(0.00001)
Patent Class FE	Yes	Yes	Yes	Yes	Yes	Yes
Foreign Patent FE	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.014	0.014	0.014	0.005	0.005	0.005
Observations	5,227,372	5,227,372	5,227,372	5,227,372	5,227,372	5,227,372

Table A.2: Heterogeneity by investor stage—Top 1%

This table repeats the analysis of Table 9 but with *Top* referring to the top 1% among patents from the same application month cohort. Standard errors are clustered by application month. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Patents and citations

	$\mathbb{1}$(Patent with VC affiliation)				$\mathbb{1}$(Top cited patent with VC affiliation)			
	(1) Early VC	(2) Late VC	(3) Early VC	(4) Late VC	(5) Early VC	(6) Late VC	(7) Early VC	(8) Late VC
$\mathbb{1}$(Recession)	-0.00196***	0.00087*	-0.00186***	0.00118***	-0.00016***	-0.00009***	-0.00016***	-0.00008***
	(0.00040)	(0.00052)	(0.00040)	(0.00032)	(0.00004)	(0.00003)	(0.00004)	(0.00003)
Log VC investment			0.00060***	0.00180***			0.00002**	0.00007***
			(0.00008)	(0.00007)			(0.00001)	(0.00001)
Patent Class FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Foreign Patent FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
P-value of difference	0.00		0.00		.217		.148	
R-Squared	0.013	0.014	0.013	0.015	0.002	0.002	0.002	0.002
Observations	5,227,372	5,227,372	5,227,372	5,227,372	5,227,372	5,227,372	5,227,372	5,227,372

Table A.2: (Continued)

Panel B: Originality and generality

	𝟙(Top originality score patent with VC affiliation)				𝟙(Top generality score patent with VC affiliation)			
	(1) Early VC	(2) Late VC	(3) Early VC	(4) Late VC	(5) Early VC	(6) Late VC	(7) Early VC	(8) Late VC
𝟙(Recession)	-0.00005**	-0.00003	-0.00005**	-0.00002	-0.00013***	0.00005	-0.00012***	0.00006
	(0.00002)	(0.00003)	(0.00002)	(0.00002)	(0.00002)	(0.00004)	(0.00002)	(0.00003)
Log VC investment			0.00002***	0.00005***			0.00005***	0.00005***
			(0.00000)	(0.00000)			(0.00000)	(0.00001)
Patent Class FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Foreign Patent FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
P-value of difference	.434		.36		0.00		0.00	
R-Squared	0.001	0.000	0.001	0.000	0.001	0.000	0.001	0.001
Observations	5,227,372	5,227,372	5,227,372	5,227,372	5,227,372	5,227,372	5,227,372	5,227,372

Table A.2: (Continued)

Panel C: Closeness to science

	𝟙(Top closeness to sci. patent w/ VC affiliation)				𝟙(Top closeness to quality sci. patent w/ VC affiliation)			
	(1) Early VC	(2) Late VC	(3) Early VC	(4) Late VC	(5) Early VC	(6) Late VC	(7) Early VC	(8) Late VC
𝟙(Recession)	-0.00009***	-0.00002	-0.00009***	0.00000	-0.00010***	0.00000	-0.00010***	0.00002
	(0.00002)	(0.00004)	(0.00002)	(0.00003)	(0.00002)	(0.00003)	(0.00002)	(0.00003)
Log VC investment			0.00001**	0.00010***			0.00001	0.00009***
			(0.00001)	(0.00001)			(0.00001)	(0.00001)
Patent Class FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Foreign Patent FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
P-value of difference	.109		0.025		0.014		0.001	
R-Squared	0.004	0.005	0.004	0.005	0.005	0.007	0.005	0.007
Observations	5,227,372	5,227,372	5,227,372	5,227,372	5,227,372	5,227,372	5,227,372	5,227,372

Table A.3: Top cited patents with VC affiliation–Interaction Model

This table repeats the analysis from Tables 4 and 9 using interactions of independent variables. The dependent variable in columns 1-3 (4-6) is an indicator for the patent being in the top 10% (1%) of patents applied for within the month by citations. The indicator for Recession is interacted with either an indicator for being a VC-affiliated patent as in Table 4 (columns 1, 4), an indicator for the firm syndicate being early specialist as in Table 9 (columns 2, 5), or an indicator for the deal itself being designated early-stage (columns 3, 6). *Log VC investment* is the log of aggregate VC investment in the U.S. startups during the month the patent was applied for. *Foreign patent FE* is an indicator variable equal to one if any of the patent assignees were not based in the U.S. *Class FE* represent class fixed effects based on the patents primary, 3-digit USPC class. Standard errors are clustered by application month. *,**, and *** denote statistical significance at the 10%, 5%, and 1%, respectively.

	$\mathbb{1}$(Top cited patent)					
	Top 10%			Top 1%		
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$(Recession) × $\mathbb{1}$(VC)	-0.01303*			-0.00665***		
	(0.00755)			(0.00245)		
$\mathbb{1}$(Recession) × $\mathbb{1}$(Early VC firm)		-0.05224**			-0.01439***	
		(0.02119)			(0.00468)	
$\mathbb{1}$(Recession) × $\mathbb{1}$(Early VC deal)			-0.02622***			-0.01047***
			(0.00842)			(0.00323)
$\mathbb{1}$(VC)	0.12141***			0.02647***		
	(0.00233)			(0.00099)		
$\mathbb{1}$(Early VC Firm)		0.11878***			0.02527***	
		(0.00291)			(0.00127)	
$\mathbb{1}$(Early VC Deal)			0.14398***			0.03541***
			(0.00312)			(0.00157)
$\mathbb{1}$(Recession)	-0.00501***	-0.00519***	-0.00507***	-0.00035**	-0.00041**	-0.00038**
	(0.00148)	(0.00150)	(0.00148)	(0.00015)	(0.00016)	(0.00016)
Log VC investment	-0.00358***	-0.00330***	-0.00344***	-0.00092***	-0.00086***	-0.00089***
	(0.00049)	(0.00049)	(0.00049)	(0.00005)	(0.00005)	(0.00005)
Class FE	Yes	Yes	Yes	Yes	Yes	Yes
Foreign Patent FE	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.063	0.061	0.062	0.031	0.030	0.031
Observations	5,227,372	5,227,372	5,227,372	5,227,372	5,227,372	5,227,372

Table A.4: Top cited patents with VC affiliation–Without Foreign Patents

Observations are at the patent level. The sample is limited to VC-affiliated patents. A patent assignee is defined as being VC-affiliated 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. The dependent variable in columns 1-2 (3-4) is an indicator for the patent being in the top 10% (1%) of patents applied for within the month by citations. Columns 1 and 3 repeat the main results from Table 4. Columns 2 and 4 omit foreign patents, which are patents in which any of the patent assignees were not based in the U.S. Standard errors are clustered by application month. *,**, and *** denote statistical significance at the 10%, 5%, and 1%, respectively.

	$\mathbb{1}$(Top cited patent with VC affiliation)			
	Top 10%		Top 1%	
	(1)	(2)	(3)	(4)
$\mathbb{1}$(Recession)	-0.00106***	-0.00197***	-0.00027***	-0.00050***
	(0.00022)	(0.00040)	(0.00006)	(0.00011)
Patent Class FE	Yes	Yes	Yes	Yes
Foreign Patent FE	Yes	No	Yes	No
Sample	All Patents	Domestic Patents	All Patents	Domestic Patents
R-Squared	0.014	0.013	0.005	0.005
Observations	5,227,372	2,654,527	5,227,372	2,654,527