Betting on Disruption: How Uncertainty Shapes the US Startup Ecosystem*

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Abstract

This paper shows that economic uncertainty boosts dynamism among US startups. I introduce news- and survey-based measures of startup-relevant uncertainty and find that uncertainty is associated with net firm creation, and net job creation among young firms. I identify the channel by demonstrating, in a real-options framework, that venture capitalists (VCs) adjust their portfolios to take advantage of uncertainty. In contrast to mature firms delaying investment when facing uncertainty, VCs increase their investment spending during periods of heightened uncertainty, but do so by funding a large number of startups at low valuations. Critically, these dynamics play out solely at the earliest funding stages, implying greater experimentation by VCs. Buoyed by increased VC funding, startups accelerate their investment in technology and labor, producing more innovation and gaining greater traction. Looking at eventual outcomes, I provide evidence that startups receiving funding during high uncertainty periods are more likely to either fail or have exits with high multiples. My results point to uncertainty playing an important role in spurring "creative destruction" by way of stimulating risky startup activity in the economy.

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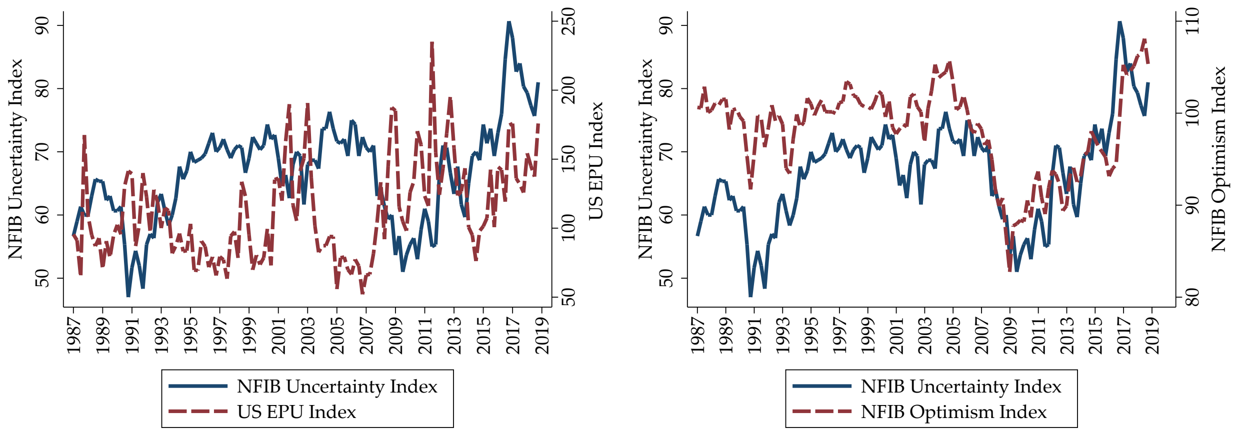
1 Introduction

A large literature has emphasized the deleterious effect of uncertainty on firm-level investment (Julio and Yook (2012), Gulen and Ion (2015)) and aggregate output and employment (Bloom (2009), Baker and Bloom (2013), and Bloom et al. (2018)). The negative uncertainty–investment relationship is grounded in real-options models of investment under uncertainty in which investment decisions are costly to reverse (Bernanke (1983), Dixit and Pindyck (1994)). This irreversibility generates an incentive for firms to "wait-and-see," leading them to withhold investment in the face of uncertainty shocks. Yet, the seminal work of Knight (1921) discusses how uncertainty is the underlying source of entrepreneurial profits, and is necessary to induce investors to fund entrepreneurs, thereby stimulating entrepreneurial entry. The notion of uncertainty also features in Schumpeter's discussion of "creative destruction," which he posits as the engine of economic growth (Schumpeter (1939, 1961)). These works motivate the possibility that uncertainty plays a role in spurring investors to finance entrepreneurial activity, boosting dynamism in the economy. In this paper, I study the link between uncertainty and the financing of entrepreneurship in the context of the US startup ecosystem.

I begin my analysis with a set of tests aimed at uncovering aggregate relationships between uncertainty and startup-related activity in the US economy. A key first step in assessing the effect of uncertainty on startup activity is to identify appropriate measures of uncertainty relevant to the economic entities that I consider. A natural candidate measure is an indicator of macro-uncertainty such as the Baker et al. (2016) EPU Index. An alternative approach is to utilize a startup-specific measure of uncertainty. One such measure is the Small Business Uncertainty Index compiled by the National Federation of Independent Businesses (NFIB). This index is formed by aggregating responses to surveys of small businesses, in which the NFIB elicits measures of small business owners' perceptions of economic uncertainty. Comparing the EPU Index to the NFIB Index reveals that they are broadly similar, but with some salient differences (see Figure 1). An examination of two major events in the last



(A) NFIB Uncertainty Index and EPU Index **(B)** NFIB Uncertainty and Optimism Indices

Figure 1. Uncertainty and Optimism Indices. This figure displays the NFIB survey-based small business uncertainty index and the Baker et al. (2016) US Economic Policy Uncertainty Index (Panel A) and the NFIB survey-based small business optimism index (Panel B).

decade illustrates this dichotomy. The onset of the financial crisis triggered a significant increase in the EPU Index, while the NFIB Uncertainty Index experienced a concurrent significant decline. On the other hand, the unexpected outcome of the 2016 US Presidential Election generated spikes in both series (Panel A). Panel B compares the NFIB Uncertainty Index with the NFIB Optimism Index (a startup-relevant "first-moment" proxy). The two series display significant positive co-movement, with their correlation coefficient exceeding 0.55. This stands in stark contrast to the strong negative correlation between first and second moments documented by existing studies on the effects of uncertainty on mature firms (see, e.g., Bloom (2009)). The figure points to significant differences in how uncertainty is perceived by small businesses relative to a commonly-used uncertainty proxy.

Motivated by these data patterns, I propose two startup-specific measures of uncertainty. The first is a survey-based industry-level variant of the aggregate NFIB Small Business Uncertainty Index, also constructed by the NFIB. I use this measure to capture a composite notion of economic uncertainty, built upon small business owners' expectations of demand, investment, and financing conditions, and the regulatory environment. As a second measure, I construct a news-based industry-level variant of the EPU Index by analyzing co-mentions of economic policy uncertainty-related keywords, startup related-keywords, and industry keywords across the same set of news articles used by Baker et al. (2016). Measuring uncertainty at the industry level is beneficial as it allows me to control for time-varying, entity-fixed unobserved factors in my specifications. With these two measures, I conduct a series of tests relating uncertainty to the extensive and intensive margins of aggregate startup activity. On the extensive margin, I find that uncertainty is associated with significant increases in firm births and deaths, with the increase in births more than offsetting the increase in deaths, implying net firm creation. On the intensive margin, I show that uncertainty is also linked to net job creation among newly-formed firms, while depressing net job creation among mature firms.[1]

I rationalize the overall evidence on the positive relationship between uncertainty and startup activity through a financing channel in which venture capitalists (VCs), the key financial intermediaries in the startup ecosystem, invest more when faced with greater uncertainty. I establish the microeconomic underpinnings of this channel using a simple real-options framework. In the framework, I show that VCs adjust their portfolios by increasing their investment in early-stage startups when uncertainty is high. This dynamic arises as VCs have the ability to stage their investments. Specifically, they can condition follow-on investments on startups achieving interim targets, which inform them about the future potential of the ventures. An increase in uncertainty implies that the likelihood of a given startup either becoming very successful, or failing, rises. Accordingly, VCs invest in more startups with the aim of finding potential disruptors while mitigating their losses on unsuccessful investments through staging. VCs' investments in early-stage ventures embed abandonment options, and these options become more valuable when uncertainty regarding eventual startup exit outcomes increases. In all, the framework points to increased experimentation by VCs when uncertainty is high, and motivates testable predictions which I take to the data.

Using a large sample of VC financing deals, and the two measures of startup-relevant uncertainty, I assess the relationship between uncertainty and VCs' investment decisions. I

[1]The result on job destruction among mature firms is consistent with studies pointing to negative effects of uncertainty on aggregate employment (see, among others, Bloom (2009)).

employ an empirical specification that captures the effects of uncertainty on VC financing while controlling for other determinants of these decisions, some of which might be correlated with uncertainty. In particular, the positive correlation between uncertainty and optimism shown in Figure 1 highlights a potential confounding effect of first moments on VCs' portfolio decisions. Simply put, any relation between VC investment and uncertainty I uncover may be attributable to an increase in the mean (first moment), and not uncertainty (second moment), of exit outcomes. I mitigate this concern by controlling for several first-moment proxies including the NFIB Optimism Index, and *Q* and *Cash Flow* of public firms in a given startup's industry, along the lines of Gompers (1995). The specification also includes a rich set of fixed effects intending to absorb unobserved heterogeneity at the levels of the startup, lead VC, financing round, and time. I find a positive relationship between uncertainty, and the probability and amount of VC financing, and a negative relationship between uncertainty and deal valuation. The economic magnitudes are notable: a one-standard-deviation increase in uncertainty is associated with an 18% relative-to-mean increase in the probability of receiving funding, while the corresponding increase in funding amount represents 16% of the mean.

A key implication of my theoretical framework is that the ability of VCs to stage their investments drives the positive relationship between VC investment in early-stage startups and uncertainty, by increasing the value of the embedded abandonment options. Put differently, the theoretical framework implies that VCs engage in greater experimentation in the face of uncertainty. I test this mechanism by separately estimating the probability of VC funding in subsamples by funding round. I find that the unconditional effects are driven solely by an increased propensity of VCs to fund ventures at the earliest stages (Seed and Series A). The response of VC investments to uncertainty in later funding stages are muted and statistically indistinguishable from zero. I also find suggestive evidence that VCs are more likely to invest in startups with less experienced founders, consistent with a greater willingness to take long-shot bets (at least initially) when uncertainty is high and these bets are either more likely to pay off with high multiples or end in failure.

To shed further light on how uncertainty affects VCs' portfolio composition decisions, I examine how deal structure varies with uncertainty. My results point to reduced syndication, evidenced by a decrease in the number of investors per round. Complementing this, I find that uncertainty is associated with an increase in the proportion of the total deal funding amount committed by the lead VC. I also study the characteristics of VCs that invest more during periods of higher uncertainty and find that experienced VCs are more likely to act aggressively when uncertainty increases. I further show that VCs which are more "central," and share common educational or career background with a startup's management team, are more likely to invest. These results suggest that soft information affects the ability of VCs to take advantage of uncertainty. In particular, VCs with lower costs of obtaining soft information on portfolio companies have the highest propensity to adjust their portfolios in response to uncertainty. Since investing more during periods of higher uncertainty entails a greater likelihood of investing in ventures that are likely to fail, the ability to detect whether a given venture is likely to fail at the earliest possible stage is crucially important. Accordingly, VCs best suited to do so respond most pronouncedly to uncertainty.

The next part of my analysis traces out the link between uncertainty and startup outcomes. I consider three sets of outcomes, startups' investment decisions, their subsequent traction, and eventual exits for investors. The theoretical framework and empirical results on VC responses imply that uncertainty eases financing constraints for startups. Consistently, I find that uncertainty is associated with increased investment by startups in R&D, technological, and human capital. Specifically, when uncertainty is high, startups are granted more patents, increase their IT expenditures, and grow their employment. I also find that uncertainty translates to increased traction, proxied by sales and search interest. Finally, I examine eventual startup outcomes and demonstrate that startups receiving their initial funding during periods of higher uncertainty are either more likely to exit in IPOs and acquisitions with high valuations, or fail. This finding provides a rational ex-post justification for VCs' response to uncertainty.

My study contributes to the literature on firm responses to uncertainty. Existing empirical papers have focused on the negative impact of uncertainty on output (Bloom (2009), Baker and Bloom (2013)) and investment by public firms (Leahy and Whited (1996), Julio and Yook (2012), Gulen and Ion (2015), and Kim and Kung (2016)) among other economic outcomes (Julio and Yook (2016), Bonaime et al. (2018)). My study is novel in examining the role of uncertainty on startup dynamics. VCs' decisions to invest in startups are fundamentally unlike mature firms' decisions to invest in irreversible capital. My work adds to this literature by demonstrating how the absence of irreversibility, such as in the presence of staging, can lead to a positive effect of uncertainty on investment. This study is closely related to those examining the role of uncertainty on firms' "growth option–" like investments, such as R&D and innovation. The evidence here is mixed, with some studies finding positive effects among public firms in the US (Stein and Stone (2013), Atanassov et al. (2015)).[2] Bhattacharya et al. (2017), on the other hand, find negative effects of policy uncertainty on innovation in a cross-country study. My work builds upon these by focusing on the economic agents most likely to benefit from increased uncertainty, examining VC portfolio decisions and startup outcomes in the US context. My results on uncertainty easing startups' financing constraints by spurring VC investment stand in contrast to studies showing financing constraints tighten for mature firms when uncertainty increases (Gilchrist et al. (2014)). Finally, my paper also adds to the growing entrepreneurial finance literature on the determinants of VCs' portfolio decisions (see Da Rin et al. (2013) for an overview). In particular, I posit uncertainty as an important factor contributing to VC experimentation (see Nanda and Rhodes-Kropf (2013, 2016a,b), Kerr et al. (2014), and Ewens et al. (2018)) with the ability of VCs to stage investments playing a key role in this dynamic (Tian (2011)). My results are also consistent with the finding that VCs' option to invest in follow-on rounds accounts for a positive relation between volatility and VC performance (Peters (2018)).

[2]These papers offer a number of theoretical explanations for the positive relationship between investment and R&D spending including the roles of sequential investment with lags (Bar-Ilan and Strange (1996, 1998)), learning about uncertain costs (Grossman and Shapiro (1986)), technical uncertainty (Pindyck (1993)), and strategic preemption (Kulatilaka and Perotti (1998)).

The remainder of the paper proceeds as follows. In Section 2, I examine how aggregate startup dynamics respond to uncertainty. Section 3 presents a theoretical framework and derives testable implications. Section 4 describes the data. Section 5 presents the results from my main analysis on the relationship between uncertainty and VC funding decisions, and Section 6 describes results on startup outcomes. Section 7 concludes.

2 Uncertainty and Aggregate Startup Dynamics

I begin my analysis gauging the relationship between uncertainty and aggregate startup dynamics. To do so, I first describe two measures of startup-relevant uncertainty. I then test how these measures correlate with firm creation and job creation among startups.

2.1 Measuring Startup-Relevant Uncertainty

2.1.1 Survey-Based Uncertainty Measure

I measure startup-relevant uncertainty using two complementary approaches. The first is a survey-based measure, constructed by the NFIB using responses to their monthly survey of small businesses. This survey has been conducted by the NFIB on a monthly basis since 1986, and participants are randomly drawn from member firms, amounting to more than 325,000 businesses. The uncertainty index is calculated by summing the percent of "don't know" and "uncertain" responses for six questions concerning small business owners' projections for demand, expansion, hiring, investment, financing, and their general economic outlook.[3] I obtain the monthly uncertainty index values for each industry in the NFIB industry classification and map them to NAICS industries for consistency across the various datasets I employ in my analyses.

[3]For more details see https://www.nfib.com/uncertainty-index-methodology/.

2.1.2 News-Based Uncertainty Measure

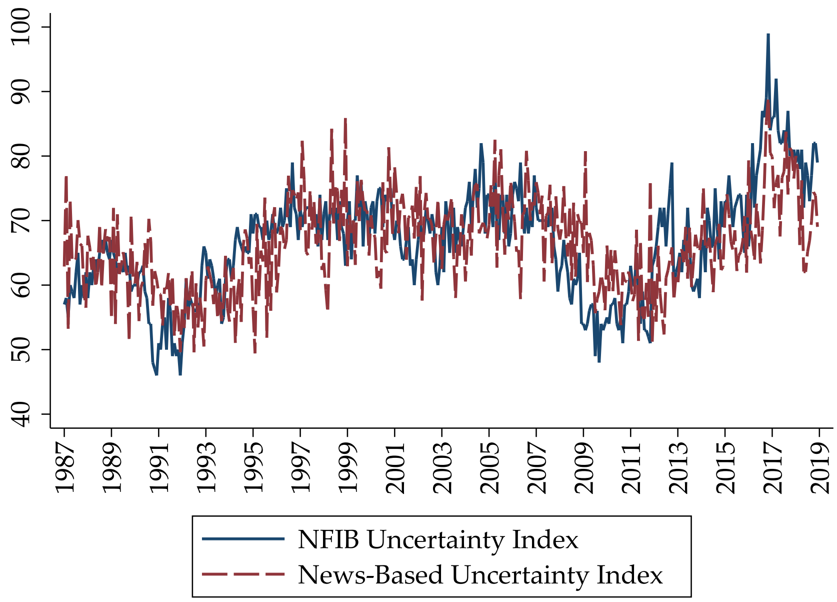
For my second measure, I modify the Baker et al. (2016), henceforth BBD, EPU news-based uncertainty index along two dimensions in order to (i) incorporate startup-relevance, and (ii) partition by industries. I begin by scraping all news articles from the same 10 leading newspapers considered by BBD and matching the NFIB survey coverage period.[4] Similar to BBD, I consider a monthly count of articles mentioning the same "uncertainty-," "economy-," and "policy-" related keywords. In order to capture startup-relevance, I add in the requirement that a flagged article should also mention "startup" or "entrepren-" in their text. To construct industry-level measures, I require articles to contain keywords for each NAICS industry and common variants.[5] I count the number of articles in a given newspaper meeting this criteria in each month, and scale by the total number of articles in each newspaper in that month. Following BBD, each newspaper-level series is rescaled to have a unit standard deviation, and mean of 100, over the entire sample period.

2.1.3 Comparing and Validating the Measures

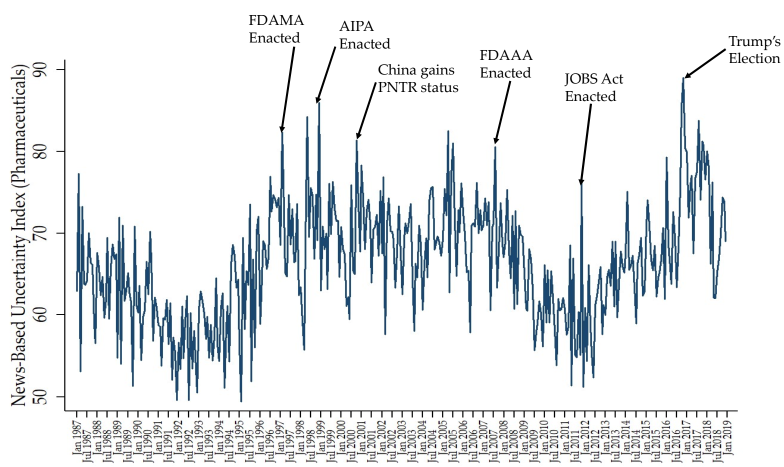
I compare the two measures (aggregated across all industries) in Figure 2. Panel A shows that they are strongly correlated (correlation coefficient of 0.76). In Panel B, I validate the news-based index by examining how it varies for one particular industry. In particular, I focus on the pharmaceutical industry. The news-based index appears to spike up around key regulatory and political events relevant to (i) the pharmaceutical industry (e.g., enactment of the FDAMA), (ii) startups in general (e.g., enactment of the JOBS Act), and (iii) major macro-events (e.g., Trump's Election), providing validation for my methodology.

[4]The 10 newspapers are *USA Today, Miami Herald, Chicago Tribune, Washington Post, Los Angeles Times, Boston Globe, San Francisco Chronicle, Dallas Morning News, New York Times, and Wall Street Journal*.

[5]Industries for which insufficient news articles are observed across all newspapers are dropped.



(A) Uncertainty Indices



(B) Pharmaceutical Industry News-Based Index

Figure 2. Measures of Startup-Relevant Uncertainty. This figure displays the survey- and news-based uncertainty indices for startups and small businesses (Panel A) and news-based uncertainty index for the pharmaceutical industry, with major events annotated (Panel B).

2.2 Uncertainty, Firm Creation, and Job Creation

In the first set of analyses, I focus on the extensive margin of startup dynamics by studying firm births, deaths, and net firm creation using longitudinal establishment-level data from the Your-economy Time Series (YTS) dataset. YTS is an establishment-level database maintained by the Business Dynamics Research Consortium at the University of Wisconsin. YTS data measure total annual employment and sales at establishments operated by public and private firms in the United States, compiled from historical files collected by Infogroup. Importantly, the YTS data link each establishment to its ultimate headquarter establishment, allowing me to distinguish between the opening (closure) of new establishments by existing firms, as opposed to true firm births and deaths. I calculate annual measures of the number of new establishments not linked to any existing headquarter establishment (firm births) and the number of existing establishments that no longer appear, and whose headquarter establishment also disappears in that year (firm deaths), in a given industry-state pair.[6] These counts are scaled by the number of establishments operating in an industry-state pair in the prior year. I estimate the following model specification:

$$Y_{i,j,t} = \beta\, Uncertainty_{j,t-1} + \theta \mathit{Controls} + FEs + \epsilon_{i,j,t}, \tag{1}$$

where $Y_{i,j,t}$ is the total firm births, deaths, and the difference between them, divided by the lagged total number of establishments in state i, industry j, and year t. *Controls* are a vector of time-varying controls at the state and industry level, including the lagged per capita personal income growth, lagged unemployment rate, the lagged industry-level NFIB Optimism Index, and the lagged Q and *Cash Flow* averaged across all Compustat firms in that industry. The variable of interest is $Uncertainty_{j,t-1}$ which refers to the lagged annual average of the industry-level survey- or news-based uncertainty indexes. The specification

[6] In unreported checks, I find that my results continue to obtain when considering only single-establishment firms.

includes fixed effects for state×industry and time, and standard errors are clustered by industry and time. Table 1 reports the results from estimating Eq. (1).

Table 1 about here.

The results in the first four columns show that uncertainty is associated with significantly higher one-year-ahead firm births and deaths, and net firm creation. The economic magnitude too is significant. A unit-standard-deviation increase in news-based uncertainty is associated with an increase in firm births of 0.566 percentage points, or 6% of the mean firm birth rate of 8.52%. The estimated impact on net firm creation is on the order of 9% of the mean net firm creation rate of 1.98%. These results are notable in providing first-pass evidence that uncertainty boosts "creative destruction" in the economy by accelerating firm births, deaths, and net firm creation.

In light of work showing that young firms account for the bulk of job creation in the US (Adelino et al. (2017)), I next examine the relationship between uncertainty and net job creation. I do so by estimating the following model specification:

$$Y_{i,j,t} = \beta Uncertainty_{j,t-1} + \theta \mathit{Controls} + FEs + \epsilon_{i,j,t}, \quad (2)$$

where $Y_{i,j,t}$ is the total job gains, job losses, and the difference between them, divided by the lagged total employment in county i, industry j, and quarter t. $\mathit{Controls}$ are a vector of time-varying controls at the state and industry level, including the lagged per capita personal income growth, lagged unemployment rate, the lagged NFIB Optimism Index, and the lagged Q and *Cash Flow* averaged across all Compustat firms in that industry. The variable of interest is $Uncertainty_{j,t-1}$ which refers to the lagged quarterly average of the industry-level survey- or news-based uncertainty indices. The specification includes fixed effects for state×industry and time, and standard errors are clustered by industry and time. Data on job creation at the county-industry-quarter level are obtained from the US Census Bureau's Quarterly Workforce Indicators (QWI) dataset. Table 2 reports the results from estimating

Eq. (2) when considering job gains, losses, and net job growth among startup firms (firms 0-1 years in age) and mature firms (firms greater than 5 years in age) as the dependent variables.

TABLE 2 ABOUT HERE.

Consistent with the extensive margin results, the estimates in the first four columns show that uncertainty is associated with significant increases in job gains and losses, and net firm job growth among startup firms. Net job growth too increases significantly among startups, while contracting significantly among mature firms, consistent with uncertainty having a negative impact on mature firms' investment. Taken together, these results merit investigation into how uncertainty differentially, and positively, affects startup activity. I do so by identifying a financing channel, whereby VC firms respond to uncertainty by increasing their investment. This, in turn, eases startups' financing constraints, reconciling the aggregate findings on uncertainty positively affecting firm and job creation among startups. I establish the underpinnings of this channel in a theoretical framework and obtain testable implications.

3 Theoretical Framework: The VC Financing Channel

I provide a simple theoretical framework to motivate predictions on how VCs adjust their portfolios when faced with greater uncertainty.

3.1 Set Up

I consider a representative risk-neutral VC firm, which invests in a set of potential early-stage startups, indexed by $i \in \{1, \cdots, N\}$. There are three periods, $t = 0, 1$, and 2. At $t = 0$, the VC decides which n of the startups to provide Series A funding to. In addition to the funding amount, which is fixed at A per startup, the VC faces a total monitoring cost, $C(n) = n^{\alpha}$, which is convex in the size of its portfolio (i.e., $\alpha > 1$).[7]

[7] This reflects the idea that monitoring resources are limited such that the costs of monitoring any given startup increases as the size of the VC portfolio increases.

A key feature of the VC's investment process is that it is able to stage its investment in its portfolio companies. That is, at $t = 1$, the VC observes a signal on the future exit value of the startup, and decides either to abandon the startup or invest in Series B. Investing in Series B incurs a cost of B per startup, and lets the startup continue operating.[8] Startups that the VC funds at Series B (does not abandon) provide an exit to the VC at $t = 2$, which is an IID payoff to the VC of $\widetilde{X_i} \equiv \widetilde{X} = x \sim N(\mu_x, \sigma_x^2)$.

Uncertainty enters my framework through σ_x, which is the volatility of eventual startup exit outcomes. An increase in uncertainty in my framework corresponds to an increase in σ_x, holding the mean payoff, μ_x constant, representing a mean-preserving spread (MPS). Failing to invest in Series B (i.e., abandoning the startup) provides a payoff of 0 to the VC.

3.2 Analysis

VC Observes Exit Payo at $t = 1$

To obtain the VC's optimal portfolio, I first lay out the VC's payoffs, $\pi(n)$, from investing in n startups under each of three cases: (i) no Series A investment, (ii) Series A investment, but no Series B investment, and (iii) Series A investment and Series B investment, assuming that at the point of decision on whether to continue to Series B. I first consider a simple case in which the VC observes $\widetilde{X} = x$ at $t = 1$ and conditions the decision to invest in Series B or abandon a venture on the observed exit payoff:

$$\pi(n) = \begin{cases} 0 & \qquad (\textit{No Investment}), \\ nx \quad \text{if } nx > nB & \qquad (\textit{Series A and B}), \\ 0 \quad \text{if } nx \leq nB & \qquad (\textit{Series A but not B}). \end{cases} \tag{3}$$

[8]This modeling is consistent with VCs having a contractual right of first refusal to invest in future funding rounds of their portfolio startups (Peters (2018)). I initially present the case where the VC observes the exit value directly at $t = 1$. I then discuss a case in which the VC sees a noisy signal of the exit value at $t = 1$. This is akin to the VC conditioning future funding rounds on a milestone, for instance, a startup achieving pre-specified sales targets or passing a clinical trial phase.

The VC thus decides to invest in Series B only if the observed exit payoff per startup exceeds the Series B investment cost, B. In light of this decision rule at $t = 1$, the VC will invest in n startups in Series A (at $t = 0$) to maximize the following:

$$\max_{n} n \times \mathrm{E}\left[\max(\widetilde{X} - B, 0)\right] - nA - n^{\alpha}. \tag{4}$$

The first-order condition of this problem helps me characterize the VC's optimal Series A portfolio size, n . It is implicitly defined by:

$$\mathrm{E}\left[\max(\widetilde{X} - B, 0)\right] = A + \alpha n^{\ \alpha \ \ 1}. \tag{5}$$

To show that the optimal portfolio size, n , increases in uncertainty, that is, in σ_x, it suffices to show that the left-hand side payoff in Eq. (5), that is, the expected payoff of the breakeven startup, increases in σ_x. Intuitively, the VC's payoff resembles that of a long call option, whose value increases when the volatility of the underlying, here $\widetilde{X}$, increases. Rewriting Eq. (5) by transforming $\widetilde{X}$ to a standard normal, I get:

$$\begin{aligned} \mathrm{E}\left[\widetilde{X} - B | \widetilde{X} > B\right] &= A + \alpha n^{\ \alpha \ \ 1}, \\ \mu_x + \frac{\sigma_x}{1 - \quad \left(\frac{B \quad \mu_x}{\sigma_x}\right)} \left[\phi\left(\frac{B - \mu_x}{\sigma_x}\right)\right] &= A + B + \alpha n^{\ \alpha \ \ 1}. \end{aligned} \tag{6}$$

This implies that the optimal portfolio size, n , is equal to:

$$n \ = \frac{1}{\alpha}\left(\mu_x - A - B + \frac{\sigma_x}{1 - \quad \left(\frac{B \quad \mu_x}{\sigma_x}\right)} \left[\phi\left(\frac{B - \mu_x}{\sigma_x}\right)\right]\right)^{\frac{1}{\alpha \ \ 1}} . \tag{7}$$

Assuming that $A + B$ is less than μ_x, that is, assuming that sufficiently profitable (in expectation) ventures exist, then $\frac{\partial n}{\partial \sigma_x} > 0$.[9] This result implies that the VC responds positively to increased uncertainty in the distribution of startup exit payoffs by increasing their optimal Series A portfolio size.

VC Observes Noisy Signal of Exit Payoff at $t = 1$

I next consider a variant in which instead of observing $\widetilde{X} = x$, the VC observes a noisy, but unbiased, signal of $\widetilde{X}$, $\widetilde{Y} = y$ before deciding whether to commit Series B funding. This signal is formed by adding a zero mean, independent normal noise, $\widetilde{\epsilon}$, with variance σ_ϵ^2 to $\widetilde{X}$, such that $\widetilde{Y} = y \sim N(\mu_x, \sigma_x^2 + \sigma_\epsilon^2)$. The VC's payoffs can be rewritten as:

$$\pi(n) = \begin{cases} 0 & \qquad\qquad\qquad\qquad\qquad (\textit{No Investment}), \\ nx \quad \text{if } n\mathsf{E}\left[\widetilde{X}|\widetilde{Y} = y\right] > nB & \quad (\textit{Series A and B}), \\ 0 \quad\;\; \text{if } n\mathsf{E}\left[\widetilde{X}|\widetilde{Y} = y\right] \leq nB & \quad (\textit{Series A but not B}). \end{cases} \tag{8}$$

The optimal portfolio size, n^*, is now implicitly defined by:

$$\mu_x + \frac{\sqrt{\sigma_x^2 + \sigma_\epsilon^2}}{1 - \Phi\left(\frac{B - \mu_x}{\sqrt{\sigma_x^2 + \sigma_\epsilon^2}}\right)} \left[\phi\left(\frac{B - \mu_x}{\sqrt{\sigma_x^2 + \sigma_\epsilon^2}}\right)\right] = A + B + \alpha n^{*\alpha - 1}. \tag{9}$$

Once again, it can be shown that $\frac{\partial n}{\partial \sigma_x} > 0$.

The framework also implies that, under reasonable conditions, the response to uncertainty is heightened for VCs with lower monitoring costs, α. The intuition behind this result is that VCs with lower monitoring costs have a lower threshold for Series A investment, and thus have a larger optimal portfolio size, n^*. When uncertainty increases, a VC with lower monitoring costs, α, thus invest in a proportionately greater number of early-stage ventures

[9] This can be shown through the fact that if $A + B$ is less than μ_x, then:

$$\phi\left(\frac{B - \mu_x}{\sigma_x}\right)\left[1 - \frac{\left(\frac{B-\mu_x}{\sigma_x}\right)\phi\left(\frac{B-\mu_x}{\sigma_x}\right)}{\left(1 - \Phi\left(\frac{B-\mu_x}{\sigma_x}\right)\right)}\right] - \phi'\left(\frac{B - \mu_x}{\sigma_x}\right)\left(\frac{B - \mu_x}{\sigma_x}\right) > 0.$$

that a VC with higher monitoring costs. I state the two core results obtained from the theoretical framework in the form of a proposition and corollary:

Proposition. *Increased uncertainty leads to more investment, that is,* $\frac{\partial n}{\partial \sigma_x} > 0$.

Corollary. *VCs with lower* α *increase investment more as uncertainty increases.*

3.3 Testable Predictions

The intuition behind the result that increased uncertainty leads to greater VC investment hinges on the fact that VCs are able to stage their investments. Higher uncertainty increases the chance that any given venture will yield a high exit return. An investment in an early-stage venture is therefore akin to investing in a call option as VCs will condition their continued investment on observing a positive signal at the interim stage. This option to abandon increases in value when uncertainty increases. The implications of my framework are consistent with VCs experimenting more at early stages when faced with heightened uncertainty. The effect is modulated by monitoring costs, as VCs with with lower monitoring costs find it worthwhile to pay these costs to obtain signals on more potential early-stage ventures when uncertainty increases. Motivated by the theoretical analysis, I obtain three testable predictions, which I take to the data:

Prediction 1. *Uncertainty increases VC investment levels.*

Prediction 2. *The VC portfolio adjustment in response to uncertainty is consistent with greater experimentation.*

Prediction 3. *The VC portfolio adjustment in response to uncertainty is more pronounced for VCs with lower monitoring costs (lower costs of obtaining soft information).*

In the subsequent sections, I provide details on the data I collect in order to test these (and associated) predictions, and describe my results.

4 Data

4.1 Venture Capital Data

I gather detailed data on venture capital firms and round-by-round information on their funding decisions from Crunchbase.[10] I include in my sample all funding rounds with complete information on the identity of investors, funding amount, type, stage, and valuation, involving US-headquartered startups who received their first round (labelled by Crunchbase as "Early-Stage Venture," corresponding mainly to either Seed or Series A rounds committed by VC firms) of VC funding over the 2005-2017 sample period. To remain in my sample, I require that each record contains complete information on the startup company name, URL, and industry and be manually matched to other datasets (detailed in the subsequent section) from which I derive other outcome and control variables. This selection process generates a sample of 30,078 unique funding rounds corresponding to 9,894 unique startups.

I construct a set variables aiming to capture various dimensions of VC funding decisions. *VC Financing Amount* is the logarithm of the dollar funding amount committed by a given VC in a round. *Valuation* is the logarithm of the dollar valuation of a round. *Investors Per Round* is the logarithm of the total number of investors in a round. *Proportion by Lead* is the proportion of the total dollar value of a round committed by the VC labelled as the "Lead." *Probability of Experienced VC* is an indicator for whether any VC in a round is experienced (defined as having made at least 3 investments in that industry in the prior 3 years).[11] *Probability of Central VC* is an indicator for whether any VC in that funding round is in the

[10] I also confirm that my main results hold in the analogous sample of VC funding rounds obtained from the VentureXpert database maintained by Refinitiv (formerly known as Thomson Reuters). I delete duplicated investment rounds following Tian (2011). This ensures that each record corresponds to a single funding round involving one (or more) VC investors and one startup. See Appendix Table A.1 for details. Comparing across the two datasets, I find that Crunchbase contains almost all (over 90%) of funding rounds meeting my sampling criteria listed in VentureXpert and also includes a number of startups and associated funding rounds not covered in VentureXpert. To verify that results are not being driven by these omitted firms, in unreported checks I rerun all my main tests on the intersection sample and find that my results continue to obtain. The use of venture capital data from Crunchbase allows me to readily link funding information to other Crunchbase datasets on venture capital firms and startups.

[11] While this cutoff is arbitrary, my results are robust to a number of sensible alternative definitions.

top tercile of eigenvector centrality for the lagged quarter. The network is constructed in each quarter among all VCs that made investments in that prior four quarters (inclusive), with two VCs being connected if they invested in the same startup in that period. A more central VC is thus, one with more connections to VCs in general, and in particular, more connections to VCs that are themselves more central. *Probability of Experienced Founder* is an indicator for whether the startup's founder is experienced (i.e., has founded or co-founded a prior startup that received at least one round of VC financing). *Probability of VC with Common Background* is an indicator for whether any member of the lead VC firm and any member of the startup's management team in the quarter of the funding round shared a common institution of employment or education (as per their individual profiles on Crunchbase).

4.2 Startup Outcomes Data

The startups in my sample are private companies and are not subject disclosure requirements. This renders obtaining even basic information on startup-level outcomes challenging. I overcome this challenge by piecing together data on startup outcomes from a number of sources. I match startups in the Crunchbase funding sample to these databases using company name and URL information. From Bureau van Dijk's Orbis Intellectual Property database, I collect startups' patenting activity. The variable *Patents* is the logarithm of one plus the total number of patents granted to the startup in a given year. From the Ci Technology Database (CITDB) I collect information on startups' expenditure on information technology. *Tech Investment Growth* refers to the annual percentage change in total dollar IT spending across all establishments linked to a given startup. The Your-economy Time Series (YTS) database, maintained by the Business Dynamics Research Consortium, contains information on total annual employment and sales at establishments operated by public and private firms in the US. Using this data, I define *Employment Growth* as the annual percentage change in the total number of employees at establishments operated by a startup, and *Sales Growth* as the annual percentage change in the total sales at establishments operated by a startup. I gauge consumer interest in a startup using Google Trends data. I construct *Search Interest* as the annual percentage change in the Search Volume Index (restricted to US searches). Finally, to gauge overall traction of a startup, I use *Trend Score*, defined the annual average Crunchbase Trend Score for a given startup. The Crunchbase Trend Score is defined as the change in a startup's Crunchbase Rank, and intends to capture fluctuations in a composite signal of a startup's prominence. A startup's Rank is based upon a proprietary algorithm accounting for its level of "connections, community engagement, funding events, news articles, and acquisitions."[12]

4.3 Control Variables

In my regression specifications, I control for several factors that are potentially correlated with both uncertainty and the outcomes of interest. At the startup firm level, I control for age, measured as the logarithm of the years since founding (based on founding date reported in Crunchbase). Following Gompers (1995), I construct industry-level controls for first moments by averaging the lagged (either quarterly or annual, depending on the specification) Q, defined as market capitalization of the firm (number of shares outstanding times end-of-period share price) plus book value of assets, minus book value of equity and deferred taxes, scaled by book value of assets, and *Cash Flow*, defined as income before extraordinary items plus depreciation and amortization, scaled by lagged book assets, across all firms in Compustat in a given startup's 3-digit NAICS industry. I also control for the NFIB Small Business Optimism index.

5 Uncertainty and VC Funding Decisions

In this section, I examine the relationship between uncertainty and VC funding decisions. In particular, I seek to verify that the predictions from the real-options framework developed in

[12]See https://about.crunchbase.com/blog/crunchbase-rank-trend-score/ for more details.

Section 3 describe observed patterns in the data, providing a rationalization for the aggregate patterns depicted in Table 1 through a financing channel. I begin by estimating a model relating the probability of a startup obtaining VC financing in a quarter to the two measures of uncertainty introduced in Section 2:

$$VC\ Financing_{i,j,t} = \alpha_i + \beta_t + \gamma Uncertainty_{j,t\ \ 1} + \theta \boldsymbol{Controls} + \epsilon_{i,j,t}, \tag{10}$$

where $VC\ Financing_{i,j,t}$ is an indicator for whether a given startup i, in industry j, received a round of VC financing in quarter t. α_i are startup firm-fixed effects and β_t are time fixed-effects (here, calendar quarter). $\boldsymbol{Controls}$ are a vector of time-varying controls at the startup firm and industry level, as described in Section 4.3. Standard errors are clustered at the industry and time levels. The variable of interest is $Uncertainty_{j,t\ \ 1}$ which refers to the lagged quarterly average of the industry-level survey- or news-based uncertainty indices. Subsequently, to characterize the relationship between uncertainty and VC financing decisions, I estimate the following regression at the startup–funding round level:

$$Y_{i,j,k,l,t} = \alpha_i + \beta_t + \gamma_k + \delta_l + \lambda Uncertainty_{j,t\ \ 1} + \theta \boldsymbol{Controls} + \epsilon_{i,j,k,l,t}, \tag{11}$$

where $Y_{i,j,k,t}$ refers to a variety of outcomes pertaining to startup i, in industry j, receiving funding of stage k, led by VC l, at time t. This specification accounts for a rich set of fixed-effects at the startup firm, time (here, calendar quarter), funding stage, and lead VC levels. Standard errors are clustered at the industry and time levels. The remaining variables are as defined in Eq. (10).

Table 3 reports results from estimating Eq. (10) and Eq. (11). Columns (1) and (2) show that across both measures of startup-relevant uncertainty, higher uncertainty is associated with a subsequently higher probability of a startup receiving funding. The coefficients reported are statistically and economically significant. A unit increase represents a one-standard deviation move in either uncertainty measures, and is associated with startups experiencing a 1.6 to 1.7 percentage point increase in the probability of receiving funding, which is between 18% and 19% of the unconditional probability of 8.8%. This confirms the central prediction from my theoretical framework that VCs respond to uncertainty by increasing their investment.

Table 3 about here.

The theoretical framework also implies that these dynamics will play out at the earliest funding stages. In Figure 3, I plot coefficient estimates and 95% confidence intervals from Eq. (10) estimated in subsamples of funding rounds. The plotted values indicate the marginal effect of a one-standard-deviation increase in the survey-based uncertainty index on the probability of VC funding. The notion that uncertainty induces VCs to increase their early-stage investments in startups is clearly borne out in the data. The bulk of the unconditional effect documented in the first two columns of Table 3 appears to be driven by increased incidence of Seed and Series A round funding. My framework implies that it is at the earliest stage of funding that VCs benefit proportionally more from increased experimentation as this is when their investments are least costly to reverse upon resolution of uncertainty (e.g., through staging). VC firms' later stage funding, in contrast, appears to be insensitive to uncertainty, suggesting higher reversibility costs and decline in uncertainty surrounding VCs' subjective assessment of the startups' eventual success probability. In all, Figure 3 provides evidence consistent with the predictions of my framework, and points to VCs adjusting their portfolios to take advantage of uncertainty.

In columns (3) through (6) of Table 3, I report coefficient estimates from Eq. (11) for the financing amount committed by the VC to the startup in that round, and the valuation of the round. The results indicate that uncertainty increases the amount committed by a VC to a given startup in a given financing round, however, it decreases the valuation at which these funds are invested. The economic magnitudes, once again, are significant. The estimate in column (3), for example, implies that a one-standard-deviation increase in uncertainty is associated with an increase in funding amount that is 16% of the unconditional

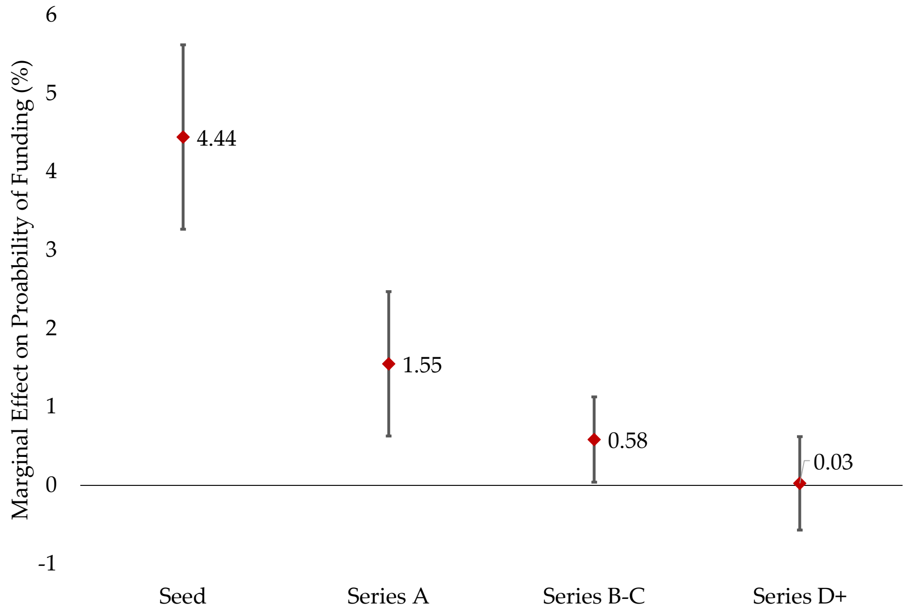


Figure 3. Marginal Effect of Uncertainty on Probability of VC Funding. This figure displays coefficients estimates and 95% confidence intervals corresponding to a one standard-deviation increase in the survey-based uncertainty index on the probability of VC funding by round.

mean amount, while the drop valuation at which the funding is committed is 14% as a share of the sample average valuation. In Table 4, I examine the relationship between uncertainty and VC financing deal characteristics.

Table 4 about here.

Table 4 reports results on the number of investors in a given round, the proportion committed by the lead VC, and the probability of a experienced VC being involved in that round. Columns (1) and (2) show that heightened uncertainty is associated with fewer investors in a given round (the effect magnitude is on the order of a decline of almost 20% in the size of the syndicate). Relatedly, results in columns (3) and (4) show that the lead VC commits a larger share of the deal, with a one-standard-deviation move in uncertainty increasing the average share by about 7% of the mean value. Lastly, the coefficient estimates reported in columns (5) and (6) indicate that more experienced VCs are more likely to take advantage of uncertainty to adjust their portfolios, as their propensity to invest increases with uncertainty is higher. These results further corroborate the theoretical predictions, showing that VCs, particularly more experienced VCs, act aggressively in adjusting their portfolios during periods of heightened uncertainty, seemingly with a goal of gaining greater exposure to potential upside.

The final set of VC funding round-level outcomes I consider relate to how soft information affects VCs' response to uncertainty. The results are reported in Table 5. The first two columns of Table 5 show that more central VCs, presumably those facing lower costs of accumulating soft information, respond more aggressively to increased uncertainty. Columns (3) and (4) provide suggestive evidence of greater experimentation as VCs are marginally less likely to invest in startups founded by experienced founders. As an additional proxy for the costs of obtaining soft information, I construct a variable indicating whether a given VC funding round involves a VC team and startup firm management team with common background. I do so by exploiting the detailed information in Crunchbase on VC firm and startup management teams' career histories and educational backgrounds. The variable *Probability of VC with Common Background* takes a value of 1 when any member of the lead VC firm and any member of the startup's management team share a common institution of prior employment or education as of that quarter. The estimated coefficients in columns (5) and (6) show a strong positive association, suggesting VCs mitigate their portfolio exposures to greater number of startups by selecting startups with which they share a common background, potentially reducing costs of monitoring and acquiring soft information.

TABLE 5 ABOUT HERE.

Taken together, the analysis in this section provides evidence that VCs adjust their portfolios to take advantage of uncertainty as predicted by the real-options framework. In the next set of tests, I investigate how uncertainty relates to startup outcomes.

6 Uncertainty and Startup Outcomes

Having established that uncertainty spurs greater VC investment in startups, in the subsequent analysis I explore how startup firms respond to uncertainty. These tests are motivated by the idea that the combination of increased VC funding and the "growth options–" nature of startup investments counteracts the usual effect of uncertainty in curtailing firm investment, thereby leading the average startup firm to invest more in response to uncertainty. I do so by considering two sets of outcomes. The first set of outcomes captures startups decisions to invest in R&D, technology, and human capital, and the second set of outcomes gauge traction. Finally, I analyze the distribution of eventual outcomes startups to determine whether startups firms which received their first funding during periods of high uncertainty provide a greater likelihood of a highly successful exits, rationalizing VC firms' investment decisions.

The regression specification relating startup-level outcomes to uncertainty is as follows:

$$Y_{i,j,t} = \alpha_i + \beta_t + \gamma Uncertainty_{j,t-1} + \theta \textit{Controls} + \epsilon_{i,j,t}, \tag{12}$$

where $Y_{i,j,t}$ refers to a startup outcome for startup i, in industry j, in year t. α_i are startup firm-fixed effects and β_t are time fixed-effects (here, year). *Controls* are a vector of time-varying controls at the startup firm and industry level, as described in Section 4.3. Eq.(12) is estimated annually, and the variable of interest is $Uncertainty_{j,t-1}$ which refers to the lagged annual average of the industry-level survey- or news-based uncertainty indices.

6.1 Investment Outcomes

First, I test the idea that increased uncertainty boosts startups' investment in R&D, technology, and human capital. Since startups, being private firms, are not required to disclose information on their R&D expenditures, I use patent grants as a proxy for R&D investment. As a proxy for technological investments, I obtain information on startups' IT expenditures, and compute the annualized percentage change. Finally, as a proxy for investment in human capital, I use the percentage employment growth across all establishments linked to a given startup. Table 6 reports results from estimating Eq. (12) for startup investment outcomes.

TABLE 6 ABOUT HERE.

Across both measures of uncertainty, I find that startups respond to heightened uncertainty by increasing their investment spending. Specifically, when uncertainty increases, startups are granted more patents, and accelerate their technological investment and employment growth. These results suggest that rather than investing less in response to uncertainty, startups, whose investments projects are more likely to resemble growth options, invest more.

6.2 Traction Outcomes

Next, I examine whether the increased investment by startups translates into greater near-term traction. I measure startup performance through three complementary approaches. First, I consider the annual growth in sales across all establishments linked to a given startup. Second, I use Google Trends data to obtain the annual percentage change in the Search Volume Index (restricted to US searches). Third, I capture a startup's overall prominence through the annual average of a startup's Crunchbase proprietary Trend Score. Table 7 reports results for these three outcomes. The results suggest that across all three measures of traction, uncertainty is associated with superior performance for the average startup. They are consistent with startups receiving more funding (Table 3) and investing more (Table 6) in response to uncertainty.

TABLE 7 ABOUT HERE.

6.3 Exit Outcomes

The final piece of analysis investigates whether startups receiving their initial round of VC investment during periods of heightened uncertainty do indeed have more uncertain exit outcomes than those receiving their initial financing when uncertainty is low. I do so by tracking

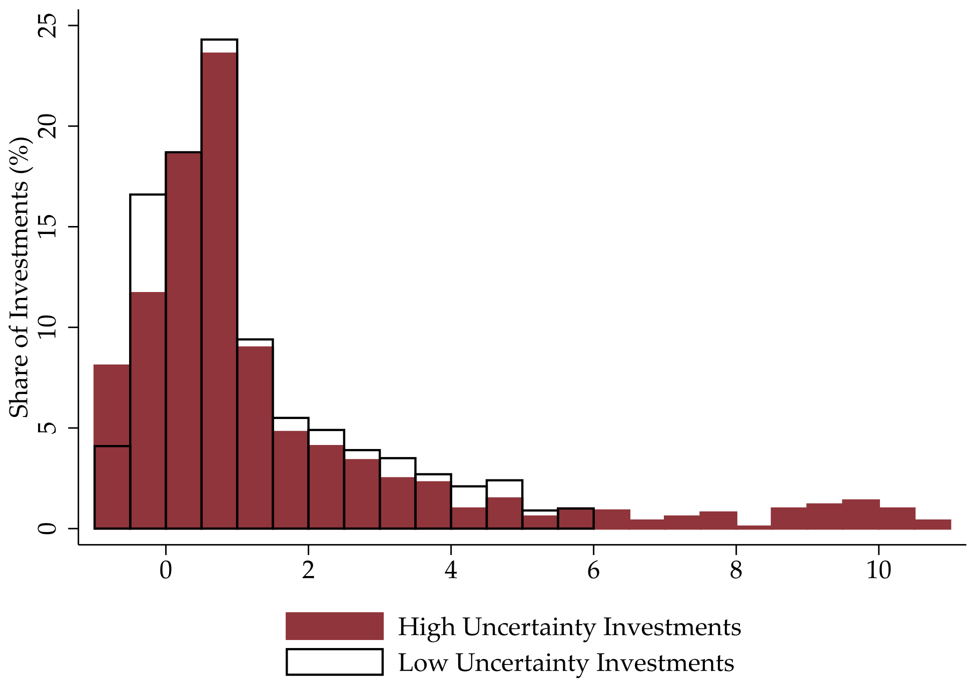


Figure 4. Distributions of Eventual Startup Outcomes. This figure displays overlaid histograms of all VC funded startup exit returns during periods of high and low uncertainty. High uncertainty periods are defined as months in which the uncertainty index is greater than 1.5 standard deviations above the unconditional mean of the survey-based uncertainty index, and low uncertainty periods are defined months in which the uncertainty index is less than 1.5 standard deviations below the unconditional mean. Startups which cease operation are coded as having an exit return of –1.

exit outcomes for startups.[13] In order to make valid comparisons of exit returns, I consider three potential outcomes: (i) IPO, (ii) acquisition, and (iii) closure. I obtain data on these outcomes from Crunchbase, and supplement them with information from the SDC Platinum database. In the case of IPOs and acquisitions, I define the exit return as the IPO or acquisition valuation divided by the valuation of the startup at its latest funding round prior to the IPO or acquisition, minus one, annualized. For firms reported as being closed in Crunchbase (and not linked to any IPOs, acquisitions, or active establishments in YTS in the subsequent year), I assume a valuation of 0, implying that they are coded as having an exit return of –1.

In Figure 4, I plot the distributions of outcomes across startups receiving their initial investment in periods of high (low) uncertainty, defined as months in which the survey-based

[13]This analysis is limited by the fact that among startups receiving their initial VC funding in the later part of my sample period, I am less likely to observe their exit outcomes as they are more likely to be under independent, private operation.

uncertainty index is greater (less) than 1.5 standard deviations above (below) the unconditional mean. Two salient implications emerge from the figure. First, the distribution of exit returns for startups receiving their first VC investment during high uncertainty periods has a long right tail, indicating high exit multiples as compared to those receiving investment during low uncertainty periods. Second, the share of investments with an exit return of –1 is almost double among startups receiving their first investment during periods of high uncertainty relative to those receiving their first investment while uncertainty is low. While I am unable to capture the actual returns earned by VC firms (and their investors), the figure provides suggestive evidence that VCs act rationally by adjusting their portfolios in response to uncertainty. The figure is also reassuring in validating that my (ex-ante) measures of uncertainty are correlated with dispersion (ex-post) in the eventual distribution of startup exit outcomes.

7 Concluding Remarks

Using novel measures of startup-relevant uncertainty, I find that uncertainty has a multi-faceted impact on the US startup ecosystem. My results suggest that uncertainty boosts startup dynamism through a financing channel as VCs adjust their portfolios to take advantage of uncertainty. Across a range of outcomes, I demonstrate that easing of financing constraints boosts startup investment in R&D, technology, and employment, gaining greater traction. Amidst a secular rise in geo-political uncertainty, my results uncover a novel dimension of how this phenomenon may impact the economy at-large. They point to uncertainty playing a key role in spurring "creative destruction" and add to our understanding by highlighting how uncertainty may have heterogeneous effects for firms at different points along age-size distribution.

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Table 1. Uncertainty and Firm Creation

This table reports output from Eq. (1). The dependent variables are the total firm births, deaths, and the difference between them, divided by the lagged total number of firms. The data are at the industry-state-year level, and aggregated from the YTS dataset. *Industry Survey Uncertainty* refers to the lagged average industry-level survey-based uncertainty index compiled by the NFIB. *Industry News Uncertainty* refers to the lagged average industry-level news-based startup-relevant uncertainty index. State-level controls include the lagged per capita personal income growth and lagged unemployment rate. Industry-level controls include the lagged Q and *Cash Flow* averaged amongst all Compustat firms in a startup's industry, and the lagged average NFIB Small Business Optimism Index in the startup firm's industry. Industries are defined at the NAICS 3-digit level. Fixed effects at the state×industry and year (time) levels are included as indicated. All regressions are estimated over the 1998–2017 period. Robust standard errors, reported in parentheses, are clustered by industry and time.

	Firm Creation					
	Firm Births		Firm Deaths		Net Firm Creation	
	Survey	News	Survey	News	Survey	News
	(1)	(2)	(3)	(4)	(5)	(6)
Industry Survey Uncertainty	0.791***		0.212***		0.579***	
	(0.003)		(0.004)		(0.004)	
Industry News Uncertainty		0.566***		0.377***		0.189***
		(0.003)		(0.004)		(0.004)
Controls						
State	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Fixed E□ects						
State × Industry	Yes	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes	Yes
Observations	44,678	44,678	44,678	44,678	44,678	44,678
R-squared	0.37	0.29	0.19	0.12	0.35	0.20

Statistical significance is indicated as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 2. Uncertainty and Job Creation

This table reports output from Eq. (1). The dependent variables are the the total job gains among firms 0 to 1 years in age, total job losses among firms 0 to 1 years in age, and the difference between the two, divided by total employment, referred to as net job growth. The final two columns report results on net job growth among firms 5+ years in age. The data are at the industry-county-quarter level, and obtained from the US Census Bureau's Quarterly Workforce Indicators dataset. *Industry Survey Uncertainty* refers to the lagged average industry-level survey-based uncertainty index compiled by the NFIB. *Industry News Uncertainty* refers to the lagged average industry-level news-based startup-relevant uncertainty index. State-level controls include the lagged per capita personal income growth and lagged unemployment rate. Industry-level controls include the lagged Q and *Cash Flow* averaged amongst all Compustat firms in a startup's industry, and the lagged average NFIB Small Business Optimism Index in the startup firm's industry. Industries are defined at the NAICS 3-digit level. Fixed effects at the state×industry and quarter (time) levels are included as indicated. All regressions are estimated over the 1993–2017 period. Robust standard errors, reported in parentheses, are clustered by industry and time.

	Job Creation							
	Firm Job Gain (Firms 0-1 Years in Age)		Firm Job Loss (Firms 0-1 Years in Age)		Net Firm Job Growth (Firms 0-1 Years in Age)		Net Firm Job Growth (Firms 5+ Years in Age)	
	Survey	News	Survey	News	Survey	News	Survey	News
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Industry Survey Uncertainty	1.513***		0.532***		0.981***		–0.512***	
	(0. 466)		(0.110)		(0.200)		(0.002)	
Industry News Uncertainty		1.235***		0.266**		0.969**		–0.532***
		(0.324)		(0.112)		(0.398)		(0.002)
Controls								
State	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects								
State × Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	251,665	251,665	251,665	251,665	251,665	251,665	251,665	251,665
R-squared	0.36	0.22	0.32	0.20	0.37	0.29	0.26	0.24

Statistical significance is indicated as follows: *** p <0.01, ** p <0.05, * p <0.1.

Table 3. Uncertainty and VC Financing

This table reports output from Eq. (10) and Eq. (11). The dependent variables are as follows. In columns (1) and (2), the dependent variable is an indicator for whether a given startup received a round of VC financing in a given quarter. In columns (3) and (4) the dependent variable is the logarithm of the dollar funding amount in a given VC financing round. In columns (5) and (6) the dependent variable is the logarithm of the dollar valuation of a given VC financing round. The data are at the startup-funding round level, and are obtained from Crunchbase. *Industry Survey Uncertainty* refers to the lagged average industry-level survey-based uncertainty index compiled by the NFIB. *Industry News Uncertainty* refers to the lagged average industry-level news-based startup-relevant uncertainty index. At the firm level, I control for the logarithm of age in years. Industry-level controls include the lagged Q and *Cash Flow* averaged amongst all Compustat firms in a startup's industry, and the lagged average NFIB Small Business Optimism Index in the startup firm's industry. Industries are defined at the NAICS 3-digit level. Fixed effects at the firm, funding round, lead VC, and quarter (time) levels are included as indicated. All regressions are estimated over the 2005–2017 period. Robust standard errors, reported in parentheses, are clustered by industry and time.

	Venture Capital Decisions					
	Probability of VC Financing		VC Financing Amount		Valuation	
	Survey	News	Survey	News	Survey	News
	(1)	(2)	(3)	(4)	(5)	(6)
Industry Survey Uncertainty	0.016***		0.026***		–0.028***	
	(0.006)		(0.003)		(0.008)	
Industry News Uncertainty		0.017***		0.011***		–0.027***
		(0.007)		(0.003)		(0.006)
Controls						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Funding Round	No	No	Yes	Yes	Yes	Yes
Lead VC	No	No	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes	Yes
Observations	226,144	226,144	30,064	30,064	30,064	30,064
R-squared	0.22	0.21	0.74	0.74	0.75	0.75

Statistical significance is indicated as follows: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 4. Uncertainty and VC Financing

This table reports output from Eq. (11). The dependent variables are as follows. In columns (1) and (2), the dependent variable is the logarithm of the total number of investors in a given financing round. In columns (3) and (4) the dependent variable is the proportion of a given VC financing round amount funded by the lead VC. In columns (5) and (6) the dependent variable is an indicator for whether any VC in that funding round is experienced (defined as having made at least 3 investment in that industry in the prior 3 years). The data are at the startup-funding round level, and are obtained from Crunchbase. *Industry Survey Uncertainty* refers to the lagged average industry-level survey-based uncertainty index compiled by the NFIB. *Industry News Uncertainty* refers to the lagged average industry-level news-based startup-relevant uncertainty index. At the firm level, I control for the logarithm of age in years. Industry-level controls include the lagged Q and *Cash Flow* averaged amongst all Compustat firms in a startup's industry, and the lagged average NFIB Small Business Optimism Index in the startup firm's industry. Industries are defined at the NAICS 3-digit level. Fixed effects at the firm, funding round, lead VC, and quarter (time) levels are included as indicated. All regressions are estimated over the 2005–2017 period. Robust standard errors, reported in parentheses, are clustered by industry and time.

	Venture Capital Decisions					
	Investors Per Round		Proportion by Lead		Probability of Experienced VC	
	Survey	News	Survey	News	Survey	News
	(1)	(2)	(3)	(4)	(5)	(6)
Industry Survey Uncertainty	–0.022***		0.025***		0.053***	
	(0.005)		(0.002)		(0.017)	
Industry News Uncertainty		–0.027***		0.011***		0.045**
		(0.003)		(0.003)		(0.026)
Controls						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Funding Round	Yes	Yes	Yes	Yes	Yes	Yes
Lead VC	Yes	Yes	Yes	Yes	No	No
Time	Yes	Yes	Yes	Yes	Yes	Yes
Observations	30,064	30,064	30,064	30,064	30,064	30,064
R-squared	0.30	0.29	0.74	0.74	0.16	0.16

Statistical significance is indicated as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5. Uncertainty and VC Financing

This table reports output from Eq. (11). The dependent variables are as follows. In columns (1) and (2), the dependent variable is an indicator for whether any VC in that funding round is in the top tercile of eigenvector centrality for the lagged quarter. In columns (3) and (4) the dependent variable is an indicator for whether the startup's founder is experienced (i.e., has founded or co-founded a prior startup that received at least one round of VC financing). In columns (5) and (6) the dependent variable is an indicator for whether any member of the lead VC firm and any member of the startup's management team in the quarter of the funding round have, in the past, shared a common institution of employment or education. The data are at the startup-funding round level, and are obtained from Crunchbase. *Industry Survey Uncertainty* refers to the lagged average industry-level survey-based uncertainty index compiled by the NFIB. *Industry News Uncertainty* refers to the lagged average industry-level news-based startup-relevant uncertainty index. At the firm level, I control for the logarithm of age in years. Industry-level controls include the lagged Q and *Cash Flow* averaged amongst all Compustat firms in a startup's industry, and the lagged average NFIB Small Business Optimism Index in the startup firm's industry. Industries are defined at the NAICS 3-digit level. Fixed effects at the firm, funding round, lead VC, and quarter (time) levels are included as indicated. All regressions are estimated over the 2005–2017 period. Robust standard errors, reported in parentheses, are clustered by industry and time.

	Venture Capital Decisions					
	Probability of Central VC		Probability of Experienced Founder		Probability of VC with Common Background	
	Survey	News	Survey	News	Survey	News
	(1)	(2)	(3)	(4)	(5)	(6)
Industry Survey Uncertainty	0.017***		–0.009*		0.026***	
	(0.003)		(0.004)		(0.004)	
Industry News Uncertainty		0.021***		–0.007*		0.016**
		(0.006)		(0.003)		(0.007)
Controls						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
Firm	Yes	Yes	No	No	Yes	Yes
Funding Round	Yes	Yes	Yes	Yes	Yes	Yes
Lead VC	Yes	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes	Yes
Observations	30,064	30,064	30,064	30,064	30,064	30,064
R-squared	0.08	0.08	0.06	0.06	0.07	0.07

Statistical significance is indicated as follows: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 6. Uncertainty and Startup Outcomes

This table reports output from Eq. (12). The dependent variables are as follows. In columns (1) and (2), the dependent variable is the logarithm of one plus the total number of patents granted to the startup in a given year. In columns (3) and (4) the dependent variable is the annual growth in technological investment of a startup, defined as percentage change in total IT spending. In columns (5) and (6), the dependent variable is annual growth in employment, defined as percentage change in number of employees of a startup. The data are at the startup level, and are obtained from Crunchbase, Ci Technology Database (CITDB), and YTS. *Industry Survey Uncertainty* refers to the lagged average industry-level survey-based uncertainty index compiled by the NFIB. *Industry News Uncertainty* refers to the lagged average industry-level news-based startup-relevant uncertainty index. At the firm level, I control for the logarithm of age in years. Industry-level controls include the lagged Q and *Cash Flow* averaged amongst all Compustat firms in a startup's industry, and the lagged average NFIB Small Business Optimism Index in the startup firm's industry. Industries are defined at the NAICS 3-digit level. Fixed effects at the firm and year (time) levels are included as indicated. All regressions are estimated over the 2005–2017 period. Robust standard errors, reported in parentheses, are clustered by industry and time.

	Startup Outcomes					
	Patents		Tech Investment Growth		Employment Growth	
	Survey	News	Survey	News	Survey	News
	(1)	(2)	(3)	(4)	(5)	(6)
Industry Survey Uncertainty	0.018***		0.051***		0.026***	
	(0.003)		(0.018)		(0.007)	
Industry News Uncertainty		0.024***		0.012***		0.017***
		(0.004)		(0.003)		(0.003)
Controls						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes	Yes
Observations	26,192	26,192	8,244	8,244	44,232	44,232
R-squared	0.24	0.24	0.38	0.37	0.38	0.37

Statistical significance is indicated as follows: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 7. Uncertainty and Startup Outcomes

This table reports output from Eq. (12). The dependent variables are as follows. In columns (1) and (2), the dependent variable is the annual sales growth reported across all establishments operated by a startup in a given year. In columns (3) and (4) the dependent variable is the search interest (measured as the year-on-year percentage change in Google Trends Search Volume Indicator) for a given startup in a given year. In columns (5) and (6) the dependent variable is the average Crunchbase trend score for a given startup in a given year. The data are at the startup level, and are obtained from YTS, Google Trends, and Crunchbase. *Industry Survey Uncertainty* refers to the lagged average industry-level survey-based uncertainty index compiled by the NFIB. *Industry News Uncertainty* refers to the lagged average industry-level news-based startup-relevant uncertainty index. At the firm level, I control for the logarithm of age in years. Industry-level controls include the lagged Q and *Cash Flow* averaged amongst all Compustat firms in a startup's industry, and the lagged average NFIB Small Business Optimism Index in the startup firm's industry. Industries are defined at the NAICS 3-digit level. Fixed effects at the firm and year (time) levels are included as indicated. All regressions are estimated over the 2005–2017 period. Robust standard errors, reported in parentheses, are clustered by industry and time.

	Startup Outcomes					
	Sales Growth		Search Interest		Trend Score	
	Survey	News	Survey	News	Survey	News
	(1)	(2)	(3)	(4)	(5)	(6)
Industry Survey Uncertainty	0.055**		0.039*		0.098***	
	(0.022)		(0.024)		(0.004)	
Industry News Uncertainty		0.042***		0.012*		0.082***
		(0.006)		(0.007)		(0.007)
Controls						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes	Yes
Observations	22,928	22,928	16,192	16,192	36,754	36,754
R-squared	0.08	0.08	0.06	0.06	0.07	0.07

Statistical significance is indicated as follows: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.1. Uncertainty and VC Financing in the VentureXpert Sample

This table reports output from Eq. (10) and Eq. (11). The dependent variables are as follows. In columns (1) and (2), the dependent variable is an indicator for whether a given startup received a round of VC financing in a given quarter. In columns (3) and (4) the dependent variable is the logarithm of the dollar funding amount in a given VC financing round. In columns (5) and (6) the dependent variable is the logarithm of the dollar valuation of a given VC financing round. The data are at the startup-funding round level, and are obtained from VentureXpert. *Industry Survey Uncertainty* refers to the lagged average industry-level survey-based uncertainty index compiled by the NFIB. *Industry News Uncertainty* refers to the lagged average industry-level news-based startup-relevant uncertainty index. At the firm level, I control for the logarithm of age in years. Industry-level controls include the lagged Q and *Cash Flow* averaged amongst all Compustat firms in a startup's industry, and the lagged average NFIB Small Business Optimism Index in the startup firm's industry. Industries are defined at the NAICS 3-digit level. Fixed effects at the firm, funding round, lead VC, and quarter (time) levels are included as indicated. All regressions are estimated over the 2005–2017 period. Robust standard errors, reported in parentheses, are clustered by industry and time.

	Venture Capital (VentureXpert)					
	Probability of VC Financing		VC Financing Amount		Valuation	
	Survey	News	Survey	News	Survey	News
	(1)	(2)	(3)	(4)	(5)	(6)
Industry Survey Uncertainty	0.022***		0.028***		-0.017***	
	(0.006)		(0.003)		(0.008)	
Industry News Uncertainty		0.012***		0.026***		-0.014***
		(0.007)		(0.003)		(0.006)
Controls						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Fixed E□ects						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Funding Round	No	No	Yes	Yes	Yes	Yes
Lead VC	No	No	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes	Yes
Observations	155,055	155,055	20,920	20,920	20,920	20,920
R-squared	0.11	0.09	0.44	0.38	0.40	0.33

Statistical significance is indicated as follows: *** p <0.01, ** p <0.05, * p <0.1.