How Smart is Smart Money?

Venture Capital Check Sizes as a Predictor of Economic Policy Uncertainty

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Abstract

This paper tests whether changes in venture capital check sizes predict future economic policy uncertainty (EPU) beyond information already captured in standard macroeconomic and financial indicators. I use monthly U.S. private-market deal data drawn from SEC Form D filings covering September 2008 through December 2024 to test whether lagged average VC check size changes predict future EPU changes at 3-, 6-, 9-, and 12-month horizons. Though I found evidence of a bivariate relationship at the aggregate level, this relationship lost significance upon introducing market and macroeconomic indicators despite thorough robustness and causality checks, confirming the null hypothesis. Further analysis at the industry level provides sparse evidence of VC predictive power of industry uncertainty but unearths that industry-specific equity volatility is particularly relevant in predicting within-industry check size changes, which I interpret as VC investment decisions responding to observable market conditions. I further explore Real Options theory and find that high-tangibility industries reduce check sizes more aggressively in anticipation of future uncertainty than low-tangibility ones which is the opposite of what the theory predicts. I hypothesize that the explanatory mechanism is pivotability, meaning tangible assets generally proxy for a company's ability to adapt to changing conditions, making VCs more sensitive to forward uncertainty in those industries, while intangible companies retain their ability to pivot and adapt.

I. Introduction

VCs often recite the same pitch when raising LP capital. They claim their superior positioning allows them to capture value in current market conditions, brag about proprietary deal flow, and flaunt years of business development and unparalleled industry expertise. While specifics may vary, the core claim remains that they have better information than everyone else. This paper asks whether that claim is actually true, at least in one dimension.

This question has largely been studied in adjacent forms using public market performance. There's a large literature in financial economics that has asked whether sophisticated intermediaries which include hedge funds, analysts, and institutional investors, outperform on the basis of private or early-stage information.[1]

However, in private markets, almost no work has been done to approach this question. Venture capital represents an interesting test case precisely because VCs truly do have different information than other investors. The specific reason I chose VCs is because they sit at an interesting informational position compared to other investors. They have much more exposure to lower-level deals as they gain insights into the operations of early-stage companies. They also conduct formal due diligence on macroeconomic and regulatory risk when analyzing investment. This "insider information" often never reaches the public but is reflected in their investment decisions and pricing. Unlike other professional investors, they sit at the lowest economic totem pole by working with startups. Startups are traditionally more instable than public companies or middle market companies, which means that they should respond more to uncertainty information than other investors. Also, their fund structures incentivize long-term thinking, given funds typically have ten-year lives and capital deployment windows of roughly five years. If any class of investor should have a reliable early-warning signal about rising macroeconomic uncertainty, it's VCs.

The main mechanism driving the theory behind this paper is Real Options theory. This theory predicts that rational investors facing irreversible commitments should reduce investment scale in the face of rising uncertainty because the value of waiting increases.[2] More uncertainty means more variation, which is why VCs are the perfect to analyze. Applying that logic to this paper, it means that if VCs correctly anticipate future uncertain conditions, average check sizes should decline before EPU increases. Therefore, my first hypothesis is that VC check sizes should signal rising uncertainty before it appears in publicly available indices.

Despite the allure of an uncertainty predictor based on private market inside information, every common current predictor (consumer sentiment, yield curves, credit spreads, IPO activity) operates through public markets. As far as I've observed, no existing uncertainty predictor draws on private investment behavior. With private markets growing rapidly in both scale and

[1] Busse, Jeffrey A., T. Clifton Green, and Narasimhan Jegadeesh. "Buy-Side Trades and Sell-Side Recommendations: Interactions and Information Content." *Journal of Financial Markets* 15, no. 2 (2012): 207–232.
[2] McDonald, Robert, and Daniel Siegel. "The Value of Waiting to Invest." Quarterly Journal of Economics 101, no. 4 (1986): 707–727.

sophistication, the question of whether private market signals contain important macroeconomic information is both timely and likely.

I first test check size changes against the Bloom, and Davis (2016) Economic Policy Uncertainty index. This, notably, is an aggregate measure of uncertainty. I chose to first analyze VC information on aggregate uncertainty because I wanted to know first if VC foresight is economy-wide vs isolated to their respective industry. I see it as a reasonable belief given the high correlation between aggregate market conditions and individual market conditions, so it seemed likely that aggregate VC activity might forecast aggregate uncertainty. In a bivariate regression, 6-month check size changes do negatively predict future EPU changes, consistent with my hypothesis, and underlining its novelty. However, this relationship almost entirely disappears entirely once I add standard financial and macroeconomic controls. The incremental R-squared contributed by check sizes beyond the current predictors is about 0.9 percentage points. Granger causality tests find no evidence of causation in either direction. These results are robust across time horizons, subsamples, alternative uncertainty measures, and non-linear specifications.

Where an aggregate analysis is important for determining the effect, the industry-level panel analysis provides a sharper picture of what actually drives check size decisions. When I match VC deal categories to volatility within Fama-French industry portfolios as a within-industry uncertainty measure, I find that lagged industry volatility significantly predicts current check size changes and aggregate EPU doesn't. This suggests that VCs are reacting to the same observable market signals available to other investors, rather than using private foresight about aggregate macroeconomic conditions.

However, this analysis would ignore that VCs truly process a different information set than typical investors. Because of this fact, I question whether Real Option Theory is observable in VC investment patterns and hypothesize that it is not. I find statistically significant evidence of this hypothesis, as the interaction between forward volatility and asset tangibility carries a coefficient of −1.300 ($p<0.05$), indicating that high-tangibility industries reduce check sizes more aggressively in anticipation of future uncertainty than their low-tangibility counterparts. This is the inverse of what Real Options Theory would predict, under which intangible, high-growth firms, whose value is concentrated in future investment opportunities rather than hard assets, should exhibit the greatest sensitivity to uncertainty.

I propose that an industry's ability to pivot drives this change. Tangible assets lock a company into a specific product, market, and cost structure, constraining its ability to adapt when conditions change. Intangible companies, such as software firms, retain the flexibility to dynamically change. VCs appear to price this strategic rigidity rather than financial recoverability, cutting check sizes more aggressively in tangible industries where portfolio companies have fewer options to navigate anticipated uncertainty. This framework also helps explain why technology was the one industry where check size changes predicted future volatility. Tech-focused VCs face less pressure to react defensively to current conditions, making their check size adjustments more likely to reflect forward-looking assessments. I note, however, the limited industry sample and the loss of biotechnology from the tangibility analysis due to a data merge issue, which limits the strength of my hypothesis.

II. Literature Review

This analysis is based on the theory from McDonald and Siegel (1986) for unpacking the impact of uncertainty on investment through Real Options theory.[3] They describe how irreversible investments decline when the investments' uncertainty rises, because the option value of waiting is greater when future payoffs are more dispersed/unknown. I specifically apply this logic to VCs, and propose that, should they actually have superior information regarding the macroeconomy or their specific industry, their investments should reflect that information. Bloom (2009)[4] provides some evidence for this and states that uncertainty shocks cause firms to pause investment and hiring, with effects that show up throughout economy. The VC setting is particularly relevant for this framework because VC investments are some of the most illiquid and irreversible commitments in the financial system.

On the VC side, Gompers and Lerner (2001)[5] document that VC investment activity is highly cyclical, with boom-bust patterns closely tied to broader financial conditions. Fang, Ivashina, and Lerner (2015)[6] find that VC activity declines sharply during financial crises. The literature on VC decision-making emphasizes the centrality of private information: Kaplan and

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[3] Ibid

[4] Bloom, Nicholas. 2009. "The Impact of Uncertainty Shocks." Econometrica 77(3): 623–685.

[5] Gompers, Paul, and Josh Lerner. 2001. "The Venture Capital Revolution." Journal of Economic Perspectives 15(2): 145–168.

[6] Fang, Lily, Victoria Ivashina, and Josh Lerner. 2015. "The Disintermediation of Financial Markets: Direct Investing in Private Equity." Journal of Financial Economics 116(1): 160–178.

Strömberg (2004)[7] and Gompers, Kaplan, and Mukharlyamov (2020)[8] document that VCs conduct systematic due diligence on macroeconomic and regulatory conditions as part of their standard investment process, which helps explain the potential for a VC connection to the general macroeconomy.

There is a relatively similar public market study in Gilchrist and Zakrajšek (2012),[9] which shows that credit spreads are actually strong public indicators of economic activity. The fact that there are existing strong benchmarks motivated me to include other controls, including credit spread, to see if VC check sizes contain incremental predictive content existing outside of already captured information.

Despite the literature on uncertainty measurement and VC behavior, I am not aware of any prior work that uses VC investment-level data, specifically check sizes aggregated from SEC Form D filings, to test whether private market activity anticipates changes in aggregate economic uncertainty.

III. Data

The primary dataset is constructed from SEC Form D filings, a mandatory SEC disclosure required within 15 days of the first sale of securities in an exempt private offering. These filings capture a broad universe of private-market capital raising activity, not just VC. To combat this, I applied a series of filters to isolate deals consistent with VC equity investment activity to over 600,000 Form D filings spanning from September 2008 to December 2024.

Specifically, I only used U.S.-based deals with disclosed amounts raised between $100,000 and $100,000,000, involving equity-only securities, operating companies with disclosed revenue, and original filings rather than amendments to avoid double-counting. After further filtering by

[7]Kaplan, Steven N., and Per Strömberg. 2004. "Characteristics, Contracts, and Actions: Evidence from Venture Capitalist Analyses." Journal of Finance 59(5): 2177–2210.
[8]Gompers, Paul, Steven N. Kaplan, and Vladimir Mukharlyamov. 2020. "What Do Private Equity Firms Say They Do?" Journal of Financial Economics 135(2): 293–312.
[9]Gilchrist, Simon, and Egon Zakrajšek. 2012. “Credit Spreads and Business Cycle Fluctuations.” American Economic Review 102(4): 1692–1720.

industry,[10] the sample contains 23,470 deals across 17 industries and 196 months. I then accounted for inflation by deflating dollars to September 2008 dollars using CPI data obtained from FRED.

One important limitation of Form D filings as a VC proxy is that issuers do not self-classify as venture-backed on the form. The filters described above are designed to select for deals structurally consistent with VC, but some non-VC private placements almost certainly remain. A second limitation is that the filing date may not precisely coincide with the date of investment, although there appears to be no systematic incentive to delay recording. A final limitation is the relatively short time series: after matching check size changes and EPU forward changes, as well as dropping missing data due to merges, aggregate-level regressions only have 49 usable months.

The primary explanatory variable is the monthly average check size, defined as total capital raised in a given month divided by the total number of deals. From this I construct lagged log changes over 1-, 3-, 6-, 9-, and 12-month horizons. Table 1 reports summary statistics.

The dependent variable in the OLS regressions is leading log three-component EPU change from Baker, Bloom, and Davis (2016).[11] They constructed the EPU by searching for policy-uncertainty-related vocabulary in the top 10 U.S. newspapers. They document that EPU spikes sharply around elections, recessions, and major policy events, and that increases in EPU depress investment, output, and employment.

I use several controls throughout the paper. For my aggregate analysis, market controls include the VIX, the Baa–Aaa credit spread, the 10-year minus 2-year Treasury term spread, and monthly S&P 500 returns, which I obtained from FRED. The Macroeconomic controls I use are the unemployment rate, the University of Michigan Consumer Sentiment Index, and monthly Leading Economic Index (LEI) growth, also from FRED. I also control for the lagged level of log EPU to capture mean-reversion, and for IPO count and IPO first day returns from Jay Ritter's dataset.[12] All controls are lagged one period relative to the check size change to reflect information available at the time of investment.

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[10] Industries excluded: Commercial Banking, Health Insurance, Hospitals and Physicians, Investing, Oil and Gas, Lodging and Conventions, Other Banking and Financial Services, Other Energy, REITs and Finance, Residential, Energy Conservation, and Electric Utilities.
[11] Baker, Scott R., Nicholas Bloom, and Steven J. Davis. 2016. "Measuring Economic Policy Uncertainty." Quarterly Journal of Economics 131(4): 1593–1636.
[12] Jay Ritter, University of Florida. Available at https://site.warrington.ufl.edu/ritter/ipo-data/.

I use a constructed uncertainty measure for my industry-level analysis. I match each VC deal category to its closest Fama-French 49-industry portfolio and then calculate monthly industry volatility using the standard deviation of daily value-weighted portfolio returns within each month.[13] I remove industry-months with fewer than five deals to reduce noise from thin cells. The resulting panel covers 11 industries, up to 196 months, and 1,002 industry-month observations at its largest.

In the final stage of my analysis, I study how VCs exhibit Real Options theory. My analysis utilizes a tangibility ratio using information from WRDS' Compustat. I divided annual Property, Plant, and Equipment (PPE) for a given industry by total assets within that industry and collapsed the result by industry-year, generating discrete rather than continuous tangibility ratios.

IV. Methodology

My baseline empirical strategy is a predictive OLS regression of forward EPU changes on lagged check size changes, conditional on the set of financial and macroeconomic controls mentioned in the section above.

$$\Delta log(U_{t+k}) = \alpha + \beta_1(\Delta CS_{t-k}) + \gamma(X_t) + \varepsilon_t$$

$\Delta \log(U_{t+k})$ is the k-period-ahead log change in the EPU index, ΔCS_{t-k} is the matched-horizon log change in average check size, and X_t describes the lagged controls. I estimate this equation at k for 3, 6, 9, and 12 months. The key coefficient is β_1 where a negative value would support the canary hypothesis (check sizes fall before uncertainty rises), an insignificant coefficient would imply that check sizes contain no incremental predictive information, and a positive coefficient would suggest we would need to rethink the mechanisms for VC investing.

[13]Specifically, for each matched Fama-French portfolio, I compute the monthly standard deviation of daily value-weighted returns, yielding a realized volatility measure. Mappings: Biotechnology with drugs; Other Health Care with health; Other Technology with software; Computers with hardware; Commercial and Business Services with business services; Manufacturing with machines; Telecommunications with telecommunication; Restaurants with meals; Retailing with retail; Construction with construction; Travel-related with transportation.

I used standard errors that are Newey-West corrected to account for serial correlation in both EPU and check using a lag length equal to the forecast horizon k.[14][15] This is important because both check sizes and EPU exhibit significant structural autocorrelation.

To test whether the bivariate result merely reflects common macro dynamics, I decompose the R-squared into a baseline model (controls only) and the full model including check sizes, computing the incremental R-squared attributable to the VC variable. I then run a Granger causality test using a 6-lag vector autoregression (VAR) in monthly check size changes and monthly EPU changes to determine whether either variable can predict the other.[16]

For robustness, I test for nonlinear effects by adding a squared check size change variable, splitting the sample into large increases and large decreases (movements above/below ±15 log points), and quartile indicator regressions. I also test across three subsamples to see if results are stable across time. These periods are the financial crisis period (2008–2010), the post-GFC expansion (2011–2019), and the COVID/post-COVID period (2020–2024).

The second part of the analysis shifts to an industry-level panel. I regress 6-month check size changes on lagged industry-specific equity volatility and lagged aggregate EPU, with industry fixed effects and clustered standard errors. This allows me to unpack whether VCs are responding to industry-specific conditions or aggregate macroeconomic policy uncertainty.

Finally, I test whether Real Options Theory manifests in VC investment behavior. I measure the mean asset tangibility for each industry-year and then regress the change in log check size on an interaction between forward industry volatility and this tangibility measure, asking whether high-tangibility industries respond differently to anticipated uncertainty than low-tangibility ones.

V. Results

A. Bivariate Results and Incremental R-Squared

[14] Newey, Whitney K., and Kenneth D. West. 1987. "A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix." Econometrica 55(3): 703–708.
[15] See note on uses of AI
[16] Ibid

I begin with a simple bivariate regression of 6-month forward EPU changes on 6-month lagged check size changes. This is shown in Table 2. The coefficient on check size changes is −0.105 ($p < 0.05$), consistent with my initial hypothesis. This means that a check size drop of 10% over the past 6 months foreshadows a rise in EPU of 1.1% in the following 6 months.

Unfortunately, the signal doesn't survive added controls. In the full-model OLS including all controls, the coefficient becomes −0.121 ($p = 0.51$). Though the point estimate is still negative, which is consistent with the expected direction, this result is insignificant. Looking to R-squared, the baseline controls-only model explains 42.1% of the variance in forward EPU changes, and adding check sizes raises this to 43.0%, giving an incremental R-squared of 0.9 percentage points.

This is the core finding of the paper. It implies that whatever connection exists between check sizes and future EPU is almost entirely explained by information already observable through public macroeconomic and financial indicators. This would suggest that VCs signal the same information that is already captured in public markets. I initially seek to validate this claim.

B. Predictions Across Horizons

I question whether this is a result of specific horizon matching. Table 3 shows the main regression results across all four matched time horizons.[17] At no point does the check size change coefficient achieve conventional significance. The 3-month coefficient is +0.072 (SE = 0.187), suggesting that, if anything, a slight positive relationship exists at small horizons, although insignificant. This is the opposite of my initial hypothesis. The 9-month coefficient is essentially zero, and the 12-month coefficient is insignificant at −0.047, meaning any result is small in magnitude and inconsistent in sign, which further undermines a structural reading of the bivariate result. I unpack this finding in section D, which contributes to the explanation why no horizon yields significant results.

As a complementary test, I ask at what lead the 6-month check size change predicts EPU at the highest bivariate correlation. The lead-lag analysis (Figure 1) shows that no lead dominates; correlations remain near zero throughout a 24-month window, with the 95% confidence intervals

[17] I test whether mismatched horizons could be driving the null hypothesis as well, finding insignificant results as reported in Appendix Table I.

containing zero at all leads. This reinforces the conclusion that the bivariate result was driven by common macro variation rather than a genuine timing relationship.

C. Robustness

Table 4 shows results across the three different subsamples. In the financial crisis period (2008–2010, N = 10), the coefficient on check size changes is −0.214 (SE = 0.484), large in magnitude but imprecisely estimated due to the small sample. In the post-GFC expansion (N = 48) and post-COVID period (N = 42), the coefficients are near zero and statistically insignificant. On the full post-GFC sample of 100 monthly observations, the coefficient is +0.002 (SE = 0.066). This provides evidence that the null result is not a consequence of any particular subsample but is rather an encompassing finding.

I question whether the data simply isn't linear in Table 5. I add a squared check size change term, finding a coefficient of +0.527 ($p < 0.10$), which would suggest that large movements in either direction are associated with rising future EPU. Economically, this could reflect that extreme VC behavior in any direction signals stress. However, the visual scatter plot included in Figure 2 provides no strong support for a U-shaped pattern, the squared term is only marginally significant, and the linear term remains insignificant in the same regression. Quartile indicator regressions likewise produce no significant pattern. I treat the quadratic finding as suggestive but not compelling.[18]

Table 6 examines alternative uncertainty measures. Substituting the VIX, the News-Based EPU component, and the credit spread for the primary EPU index produces qualitatively identical results: check size changes predict none of these alternative uncertainty proxies at conventional significance levels. This rules out the possibility that the null result is specific to the Baker-Bloom-Davis EPU construction.

D. Granger Causality and Reverse Regression

One potential concern is that both check sizes and EPU move together because both respond to underlying macroeconomic shocks. I unpack this in Table 7 by performing Granger causality tests using a 6-lag bivariate VAR in monthly check size and EPU changes. Neither variable Granger-causes the other: the p-value for the test that check sizes do not Granger cause

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[18] See Appendix Figure I

EPU is 0.783, and the p-value for the reverse test is 0.935. The two series share common macroeconomic dynamics, as evidenced by several significant controls in the forecasting regressions in Section A and B, but neither contains information about the other beyond those common factors.

Referencing Section B, check size changes show strong mean reversion at the monthly frequency. As shown in VAR estimates, the own-lagged coefficients on monthly check size changes at lags 1 through 4 are all significant and negative, ranging from −0.795 to −0.266. This means that large positive check size months are followed by negative months, and vice versa. This quick mean reversion implies that any signal embedded in a single month's check size movement dissipates quickly, making it unlikely that multi-month change variables would carry reliable directional information about EPU at horizons of 3 to 12 months.

I sought more explicit results regarding the nature of the relationship between EPU and check size, so I tested the reverse relationship in Table 8. Here I regress current check size changes on lagged EPU changes at the same four horizons used in the forward regressions. None of the lagged EPU coefficients are significant, consistent with the Granger test. This rules out the hypothesis that VCs cut check sizes after published EPU measurements rise.[19] Combined with the null forward result, the picture that emerges is one of contemporaneous movement driven by shared macro sensitivity, rather than any directional informational relationship between the two series.

E. Deal Count as an Alternative Signal

When VCs become cautious about the macroeconomic environment, they face two behavioral levers: they can write smaller checks (the intensive margin) or they can write fewer checks (the extensive margin). The check size regressions test the intensive margin; I run identical specifications for the log change in deal count in Table 9. The results are qualitatively the same: deal count changes do not significantly predict forward EPU at any horizon conditional on controls. The extensive margin carries no more predictive content than the intensive margin.

F. Industry-Level Analysis

[19] See Appendix Figure II

The aggregate null result raises an interesting question: what are VCs responding to? I test whether they could be responding to their own industry conditions, rather than to the aggregate economy. For example, a doctor evaluating a biotech company and a software investor evaluating an enterprise SaaS business may be reacting to industry-specific information that does not aggregate cleanly into a macro signal.

Table 10 presents a panel regression of 6-month within-industry check size changes on lagged industry-specific equity volatility, maintaining controls but substituting VIX for other industry volatility and adding the log of industry returns, with industry fixed effects and errors clustered at the industry level. Lagged industry volatility enters with a coefficient of −0.151 (SE = 0.041, $p < 0.01$) meaning periods of elevated industry equity volatility are followed by smaller check sizes in that industry six months later. The check size change coefficient is small and insignificant (−0.024, SE = 0.025). Aggregate EPU is also insignificant.

The horse-race regression (Table 11) includes both lagged aggregate EPU and lagged industry volatility simultaneously. Industry volatility remains significant at the 5% level (−0.278, SE = 0.088), while aggregate EPU does not survive (−0.310, SE = 0.254). The within-R-squared rises from 1.0% with EPU alone to 1.5% when both variables are included, with the incremental improvement driven entirely by industry volatility.

Figure 3 plots the industry coefficient on 6-month check size changes from individual industry regressions predicting industry volatility. Each point represents a separate regression for that industry, with 95% confidence intervals. The coefficients are mixed in sign, negative for Restaurants, Other Technology, and Other Health Care, and positive for Manufacturing, Commercial Services, and Biotechnology. Only Other Technology is statistically significant ($p<0.05$), shown in red, with a negative coefficient and consistent with my initial hypothesis, declining check sizes in tech predict rising industry volatility. The remaining five industries are all insignificant, and there is no systematic cross-industry pattern.

These industry-level results suggest that VC investors are updating their check sizes in response to observable industry equity volatility, a public market signal, rather than to private information about future aggregate policy uncertainty. One question this raises is whether the nature of industry assets affects how VCs respond to uncertainty.

G. Asset Tangibility and Real Options

Real Options theory predicts that firms facing irreversible investments should reduce investment when uncertainty rises because the option value of waiting increases when future payoffs are more uncertain. However, this prediction assumes investments are equally irreversible across all industries. In practice, industries with higher tangibility have more physical assets to act as collateral and therefore should experience less shock in pricing should the theory hold.

Table 12 tests this prediction directly. The interaction term of future volatility and tangibility has a coefficient of −1.300 ($p < 0.05$), showing that when forward volatility is high, high-tangibility industries cut check sizes more aggressively than low-tangibility ones. This is the opposite of what Real Options Theory predicts because higher tangibility industries have more recoverable collateral

VI. Discussion

My central finding is the null hypothesis. I find that changes in VC check sizes do not contain incremental predictive information about future economic policy uncertainty once standard macroeconomic and financial indicators are controlled for, evidenced by the null across different forecast horizons, uncertainty proxies, subsamples, and both linear and non-linear tests. The bivariate predictive relationship is entirely explained by common macro dynamics.

This finding has a few interpretations. The most obvious is that VCs do not, in fact, possess superior macroeconomic foresight that they act on through check size adjustments. If VCs were actually operating with genuine private information about rising uncertainty, we would expect the clearest signal to emerge in low-tangibility industries, where investments are most irreversible and the option value of waiting is highest. Instead, the predictive relationship between check sizes and forward volatility is strongest in high-tangibility industries, where assets can be partially salvaged and the odds of losing the entire investment decrease.

The strong mean-reversion in check size changes also makes it unlikely that a signal would be seen at multi-month horizons even if individual VCs had private information. This could be due to the issue of averaging heterogeneous investment decisions across large amounts of deals, which may wash out any individual level early warning. However, even at a 1-month horizon, we note the null hypothesis.

The industry-level results add nuance to the aggregate null. VCs appear to adjust check sizes in response to industry equity volatility, which is a public signal. This makes sense given that VCs are heavily concentrated in few industries, and the information that they utilize is a composite of public and private industry operational information. It also suggests that the aggregate check size series, which pools across heterogeneous industries, may lose information that is present at the industry level.

The nonlinear finding, a marginally significant positive coefficient on squared check size changes, provides some weak evidence consistent with extreme VC behavior conveying information. If very large movements in either direction are more likely to reflect genuine uncertainty rather than routine portfolio rebalancing, one might expect a U-shaped predictive relationship. However, this result does not hold up robustly (other measures are explored in Table 5).

There are a few potential reasons we might see more tangible industry check sizes responding more strongly to uncertainty. The first relates to debt financing substitution. With stable economic conditions, founders can substitute between debt solutions and VC equity investments. In uncertain times, if a company is seeking VC equity investment, it would mean that they could not secure financing, resulting in a negative signal of the quality of the deal. Increased demand for VC equity coupled with worse deals could push check size down. However, we would expect this to also respond to current uncertainty, unless banks only acted on foresight rather than current economic conditions. For this reason, I dismiss this conclusion.

The second reason, which I find more likely, is that real assets can signal difficulty in pivoting. Companies in intangible industries (namely software companies) can easily pivot or iterate on a product should they not be finding the results they seek. An investment in a highly tangible industry (Construction) has no pivot power, which means that the VC must be confident if not certain of the investment's future value. Biotech would be the industry that would have most cleanly illuminated the feasibility of this hypothesis because it is both low tangibility and low pivotability. This makes it the ideal boundary case for distinguishing pivotability as the operative mechanism rather than tangibility alone. However, I noticed it was dropped due to a Compustat issue where "Biotechnology" and "Pharmaceuticals" shared the same four-digit SIC code but were labeled differently across datasets, so the merge silently dropped that industry from the sample in Table 12. This is worth flagging: the current result is provisional precisely because the missing industry is the one whose inclusion would most directly test the framework. While there is not sufficient time to explore this option and map it by Table 12's future analysis by industry, I would imagine that the addition of Biotechnology/Pharmaceuticals would likely drop the significant result and reject the null hypothesis. Unfortunately, there was not sufficient time to fix and test this before the final deadline.

My pivotability hypothesis also helps explain why technology was the one industry where check size changes predicted future volatility. Because software companies can pivot more easily than other companies, tech VCs face less pressure to react defensively to current uncertainty. In essence, they are investing in the team. When they do cut checks, it is more likely a forward-looking signal that conditions are expected to deteriorate than a response to current uncertainty. In less pivotable industries, VCs cut reactively, making their check size changes contemporaneous with volatility rather than predictive of it.

VII. Conclusion

This paper investigates whether VC check sizes serve as a leading indicator of economic policy uncertainty. Using 16 years of SEC Form D-based deal data matched to the Baker, Bloom, and Davis EPU index, I find that check size changes predict future EPU in a simple bivariate regression but not once observable macroeconomic and financial conditions are controlled for. The incremental informational contribution of check sizes is negligible. Granger causality tests confirm the absence of causal predictive content in either direction. Industry-level analysis reveals that VC check size behavior is driven by observable equity volatility within the investor's own industry, not by private foresight about aggregate policy uncertainty.

My tangibility analysis provides further insight into the mechanisms motivating VC investment decisions. Real options theory predicts that investors facing irreversible commitments should be most sensitive to rising uncertainty, yet the data show the opposite pattern. I found that high-tangibility industries reduce check sizes more aggressively in anticipation of future uncertainty than low-tangibility ones. I hypothesize that this difference reflects high tangibility being a proxy for lower ability to pivot. I suggest that tangible assets lock firms into specific products, markets, and cost structures, constraining their ability to adapt when conditions change. Intangible companies, particularly in software, retain the flexibility to iterate or reposition entirely. This framework also explains why technology was the only industry where check size changes predicted future volatility: because software companies can pivot, tech VCs face less pressure to react defensively to current conditions, making their check size adjustments more likely to reflect forward-looking forecasts rather than just current information.

I can't conclude that VCs possess meaningful private information about future aggregate uncertainty beyond what is available in public markets. I have a few ideas about what the null hypothesis could mean. It may reflect that VCs genuinely lack private information, that they possess it but do not act on it through check size, or that the pooling across investors masks any actual heterogeneity in talented VC skillsets. However, this paper probes questions of how VCs shape their investments in response to the nature of these investments. Moving forward, first, I would like more granular deal-level data could allow for individual VC-level analysis, which might reveal heterogeneity across investors even if the aggregate signal is weak. Second, I think that a direct test of the pivotability hypothesis would benefit from resolving the Compustat merge issue that excluded biotechnology, an industry that is both low-tangibility and low-pivotability, and whose inclusion could materially alter the tangibility interaction result. Third, I think a longer time series would allow more powerful tests of subsample stability and would better capture variation across full business cycles. Finally, I think that it would be worthwhile in future work to construct a more direct measure of strategic flexibility at the industry or firm level, moving beyond asset tangibility as a proxy, to test whether pivotability rather than financial irreversibility is the key factor in VC investment decisions under uncertainty.

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Table 1:

Summary Statistics

Panel A reports deal-level statistics. Panel B reports monthly time-series statistics.

Variable	**N**	**Mean**	**Std. Dev.**	**Min**	**p25**	**Median**	**p75**	**Max**
Panel A: Deal-Level Data (N = individual VC investments)								
Number of Deals	23470	—	—	—	—	—	—	—
Number of Industries	17	—	—	—	—	—	—	—
Number of Months	196	—	—	—	—	—	—	—
Deal Size (USD millions, nominal)	23470	3.54	9.11	0.10	0.33	1	3.00	100
Deal Size (USD millions, real 2008$)	23470	3.19	8.53	0.07	0.30	0.89	2.58	99.28
Panel B: Monthly Time-Series Data (N = months)								
EPU Index (level)	196	139.98	43.46	71.26	108.31	134.09	160.52	350.46
Log EPU	196	4.90	0.29	4.27	4.68	4.90	5.08	5.86
6m Change in Log Check Size	190	-0.01	0.40	-1.92	-0.23	-0.03	0.23	2.93
VC Deals per Month	196	119.74	36.78	6	93.5	124	144.5	222
VIX	196	19.85	8.78	10.13	14.10	17.52	22.53	62.67
S&P 500 Monthly Return	107	0.00	0.00	-0.01	0.00	0.00	0.00	0.01
Credit Spread (Baa-Aaa, ppts)	196	1.05	0.46	0.55	0.76	0.95	1.15	3.38
Term Spread (10y-2y, ppts)	196	1.12	0.99	-0.93	0.26	1.17	1.88	2.83
Unemployment Rate (%)	196	6.03	2.31	3.4	3.95	5.25	7.95	14.8
Consumer Sentiment Index	196	79.44	13.17	50	69.75	77.55	91.95	101.4
LEI Monthly Growth (%)	125	0.01	0.18	-0.57	-0.07	0.01	0.09	1.00

Notes: Sample period September 2008 to December 2024. Dollar amounts in real September 2008 dollars. EPU from Baker, Bloom, and Davis (2016). Deal-level data from SEC Form D. Industries exclude Commercial Banking, Health Insurance, Hospitals and Physicians, Investing, Oil and Gas, Lodging and Conventions, Other Banking and Financial Services, Other Energy, REITS and Finance, Residential, Energy Conservation, and Electric Utilities.

Table 2:

VARIABLES	(1) Baseline	(2) CS Only	(3) Full Model
Δ Log Check Size 6M		-0.101**	-0.121
		(0.0409)	(0.183)
VIX	-0.0116		-0.00890
	(0.0203)		(0.0197)
Credit Spread	-0.562		-0.576
	(0.437)		(0.463)
Term Spread	-0.807*		-0.775**
	(0.437)		(0.309)
S&P 500 Return	38.56		41.58**
	(28.39)		(20.45)
Unemployment	0.231		0.192
	(0.379)		(0.396)
Consumer Sentiment	-0.0315		-0.0352
	(0.0208)		(0.0351)
LEI Growth	0.289		0.398
	(0.392)		(0.320)
Log EPU	-0.0285		-0.104
	(0.274)		(0.288)
IPO Count	-0.0134		-0.0133
	(0.0101)		(0.0147)
IPO Return	0.00249		0.00289
	(0.00350)		(0.00339)
Constant	3.522	-0.00606	4.349
	(3.518)	(0.0339)	(5.637)
Observations	49	184	49
R-squared	0.421		

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Regression of 6-month forward EPU on 6-month log check size change. Column 1 has baseline macro/financial controls only. Column 2 has check size changes alone for the full 184-month sample. Column 3 has full specification adding check size changes to all controls. Controls are lagged one month. Standard errors are Newey-West.

Table 3:

VARIABLES	(1) 3-Month	(2) 6-Month	(3) 9-Month	(4) 12-Month
Δ Log Check Size 3M	0.0723			
	(0.187)			
Δ Log Check Size 6M		-0.121		
		(0.183)		
Δ Log Check Size 9M			0.000312	
			(0.0798)	
Δ Log Check Size 12M				-0.0467
				(0.0799)
VIX	-0.0164	-0.00890	0.00558	-0.0284**
	(0.0176)	(0.0197)	(0.0190)	(0.0135)
Credit Spread	-0.0261	-0.576	0.346	0.580*
	(0.439)	(0.463)	(0.371)	(0.337)
Term Spread	-0.480	-0.775**	0.357	-0.213
	(0.426)	(0.309)	(0.320)	(0.305)
S&P 500 Return	51.34***	41.58**	30.52	72.68**
	(18.41)	(20.45)	(18.51)	(29.76)
Unemployment	0.109	0.192	-0.702***	-0.319
	(0.330)	(0.396)	(0.246)	(0.293)
Consumer Sentiment	-0.00365	-0.0352	-0.0373**	-0.0119
	(0.0154)	(0.0351)	(0.0182)	(0.0245)
LEI Growth	0.378	0.398	0.181	0.511*
	(0.345)	(0.320)	(0.269)	(0.286)
Log EPU	-0.460*	-0.104	-0.313	-0.229
	(0.243)	(0.288)	(0.196)	(0.145)
IPO Count	-0.0276**	-0.0133	-0.00776	-4.09e-06
	(0.0110)	(0.0147)	(0.0134)	(0.00922)
IPO Return	0.00562	0.00289	0.00715**	-0.000661
	(0.00362)	(0.00339)	(0.00275)	(0.00406)
Constant	2.848	4.349	7.506***	3.753
	(2.772)	(5.637)	(2.238)	(3.439)
Observations	49	49	49	49

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Regression of EPU on log check size changes by horizon. The full macroeconomic and financial control set included throughout, all lagged one month. Standard errors are Newey-West.

Table 4:

VARIABLES	(1) Crisis	(2) Post-GFC	(3) Post-COVID	(4) Full
Δ Log Check Size 6M	-0.214	0.00865	0.0119	0.00152
	(0.484)	(0.145)	(0.0473)	(0.0658)
Lag EPU 1M	0.459*	0.117	0.130	-0.0214
	(0.189)	(0.237)	(0.136)	(0.196)
VIX	-0.0248	-0.0190	-0.00935	-0.00821
	(0.0167)	(0.0220)	(0.00581)	(0.00679)
Credit Spread	2.266	0.358	-0.875***	-0.128
	(1.863)	(0.453)	(0.131)	(0.169)
Unemployment	-0.107	-0.212	-0.0844***	-0.0325
	(0.147)	(0.167)	(0.0259)	(0.0228)
S&P 500 Return	-29.52	27.75	8.662	15.21
	(53.01)	(24.90)	(8.118)	(9.534)
Constant	-3.863**	0.388	0.653	0.527
	(1.181)	(1.436)	(0.491)	(0.807)
Observations	10	48	42	100

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: I regressed EPU on 6 month lagged log check sizes for subsamples including the Great Financial Crisis (2008-2009), post-GFC (2010-2024), post-COVID (2020-2024), and the full sample. I used a limited set of controls, all lagged one month, including lagged EPU, VIX, credit spread, unemployment, and S&P 500 return. Standard errors are Newey-West.

Table 5:

VARIABLES	(1) Linear	(2) Categorical	(3) Quartiles	(4) Quadratic
Δ Log Check Size 6M	-0.121			-0.119
	(0.183)			(0.156)
Δ Log Check 6M Squared				0.527*
				(0.294)
Check Size Quartile 2			-0.181	
			(0.165)	
Check Size Quartile 3			-0.177	
			(0.183)	
Check Size Quartile 4			-0.0859	
			(0.174)	
Top 15% Check Decreases		0.218		
		(0.144)		
Top 15% Check Increases		0.129		
		(0.0785)		
VIX	-0.00890	-0.0183	-0.0162	-0.0124
	(0.0197)	(0.0164)	(0.0177)	(0.0176)
Credit Spread	-0.576	-0.587	-0.542	-0.477
	(0.463)	(0.448)	(0.507)	(0.521)
Term Spread	-0.775**	-0.828***	-0.828**	-0.742**
	(0.309)	(0.262)	(0.312)	(0.318)
S&P 500 Return	41.58**	31.91	29.46	35.61*
	(20.45)	(22.05)	(19.79)	(18.50)
Unemployment	0.192	0.162	0.217	0.151
	(0.396)	(0.366)	(0.403)	(0.400)
Consumer Sentiment	-0.0352	-0.0448	-0.0354	-0.0369
	(0.0351)	(0.0324)	(0.0359)	(0.0334)
LEI Growth	0.398	0.329	0.447	0.378
	(0.320)	(0.320)	(0.339)	(0.334)
Log EPU	-0.104	-0.0504	-0.0559	-0.0821
	(0.288)	(0.252)	(0.285)	(0.277)
IPO Count	-0.0133	-0.0124	-0.0140	-0.0139
	(0.0147)	(0.0152)	(0.0144)	(0.0148)
IPO Return	0.00289	0.00374	0.00291	0.00383
	(0.00339)	(0.00333)	(0.00306)	(0.00357)
Constant	4.349	5.214	4.277	4.473
	(5.637)	(5.098)	(5.745)	(5.305)
Observations	49	49	49	49

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Tests for non-linear relationships between 6-month VC check size changes and future EPU. Column 1 has the baseline linear model. Column 2 has categorical indicators for large

Table 6:

VARIABLES	(1) EPU	(2) VIX	(3) News EPU	(4) Credit Spread
Δ Log Check Size 6M	-0.121	-3.925	-60.06	-0.104
	(0.183)	(2.776)	(58.52)	(0.0713)
VIX	-0.00890	0.150	0.811	0.00893
	(0.0197)	(0.411)	(5.434)	(0.0101)
Credit Spread	-0.576	-13.00	-138.8	-0.874**
	(0.463)	(10.97)	(119.5)	(0.327)
Term Spread	-0.775**	9.750	-121.8	-0.0445
	(0.309)	(8.736)	(88.06)	(0.236)
S&P 500 Return	41.58**	927.6	14,324*	27.45
	(20.45)	(1,251)	(7,487)	(21.75)
Unemployment	0.192	-20.53*	-28.15	-0.320
	(0.396)	(11.11)	(119.9)	(0.261)
Consumer Sentiment	-0.0352	-2.198*	-13.82	-0.0224
	(0.0351)	(1.242)	(10.95)	(0.0219)
LEI Growth	0.398	3.201	109.8	0.221
	(0.320)	(6.940)	(80.41)	(0.182)
Log EPU	-0.104	-0.856	-49.70	-0.179
	(0.288)	(6.408)	(89.95)	(0.162)
IPO Count	-0.0133	-0.171	-2.781	0.000243
	(0.0147)	(0.319)	(4.028)	(0.00640)
IPO Return	0.00289	0.0680	0.782	0.000627
	(0.00339)	(0.0628)	(0.993)	(0.00145)
Constant	4.349	306.1*	1,899	5.013
	(5.637)	(162.5)	(1,786)	(3.684)
Observations	49	49	49	49

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: This is a 6-month forecast regression with different dependent variables. Column 1 uses Baker-Bloom-Davis EPU, column 2 uses VIX, column 3 uses the newspaper-based EPU component, and column 4 uses the Baa-Aaa credit spread. Full controls included. All controls lagged one month. Standard errors are Newey-West.

Table 7:

VARIABLES	(1) delta_cs_1m	(2) delta_epu_1m
Lag 1 Δ Check 1M	-0.794***	0.00730
	(0.0723)	(0.0457)
Lag 2 Δ Check 1M	-0.627***	-0.00987
	(0.0920)	(0.0582)
Lag 3 Δ Check 1M	-0.441***	0.00427
	(0.0999)	(0.0631)
Lag 4 Δ Check 1M	-0.266***	-0.0489
	(0.0987)	(0.0624)
Lag 5 Δ Check 1M	-0.109	0.0159
	(0.0888)	(0.0562)
Lag 6 Δ Check 1M	-0.0766	-0.000212
	(0.0687)	(0.0434)
Lag 1 Δ EPU 1M	-0.0368	-0.371***
	(0.115)	(0.0728)
Lag 2 Δ EPU 1M	-0.00129	-0.235***
	(0.125)	(0.0792)
Lag 3 Δ EPU 1M	-0.0897	-0.312***
	(0.126)	(0.0800)
Lag 4 Δ EPU 1M	-0.107	-0.144*
	(0.126)	(0.0798)
Lag 5 Δ EPU 1M	0.0388	-0.00671
	(0.124)	(0.0786)
Lag 6 Δ EPU 1M	-0.0619	-0.00415
	(0.116)	(0.0736)
Constant	-0.00966	-0.00201
	(0.0206)	(0.0130)
Observations	189	189

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: Bivariate Estimation of monthly log-changes in check size in column 1 and log-changes in EPU in column 2. No evidence of Granger causality between VC check sizes and EPU.

Table 8:

VARIABLES	(1) Past 3m EPU	(2) Past 6m EPU	(3) Past 9m EPU	(4) Past 12m EPU
Δ Log EPU 12M				-0.137
				(0.136)
Δ Log EPU 9M			-0.0444	
			(0.122)	
Δ Log EPU 6M		0.157		
		(0.167)		
Δ Log EPU 3M	-0.0859			
	(0.171)			
VIX	0.00528	0.00595	0.00646	0.00627
	(0.0306)	(0.0315)	(0.0324)	(0.0329)
Credit Spread	-0.150	-0.221	-0.119	-0.154
	(0.454)	(0.500)	(0.454)	(0.477)
Term Spread	-0.0133	-0.114	0.0584	-0.0340
	(0.309)	(0.353)	(0.279)	(0.343)
S&P 500 Return	18.42	23.36	18.28	22.29
	(26.14)	(30.04)	(25.29)	(26.17)
Unemployment	0.00767	0.108	-0.0489	0.0443
	(0.255)	(0.290)	(0.212)	(0.250)
Consumer Sentiment	-0.0214	-0.0167	-0.0238*	-0.0195**
	(0.0128)	(0.0121)	(0.0123)	(0.00946)
LEI Growth	0.816**	0.855**	0.803**	0.873**
	(0.402)	(0.399)	(0.358)	(0.342)
IPO Count	0.00986	0.00980	0.00949	0.00939
	(0.00825)	(0.00863)	(0.00869)	(0.00709)
IPO Return	0.00180	0.00183	0.00236	0.00270
	(0.00400)	(0.00447)	(0.00470)	(0.00472)
Constant	1.979	1.213	2.352	1.643
	(1.772)	(1.898)	(1.635)	(1.372)
Observations	49	49	49	49

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Regression of EPU on Check Sizes. Controls used are lagged VIX, credit spread, term spread, S&P 500 return, unemployment, consumer sentiment, LEI growth, IPO count, and IPO first-day returns, and lagged one month. Standard errors are Newey-West.

Table 9:

VARIABLES	(1) 3-Month	(2) 6-Month	(3) 9-Month	(4) 12-Month
Δ Deal Count 3M	0.114			
	(0.214)			
Δ Deal Count 6M		-0.368		
		(0.350)		
Δ Deal Count 9M			-0.128	
			(0.191)	
Δ Deal Count 12M				0.150
				(0.188)
VIX	-0.0145	-0.0115	0.00324	-0.0268*
	(0.0180)	(0.0156)	(0.0204)	(0.0139)
Credit Spread	-0.0622	-0.489	0.377	0.565
	(0.414)	(0.359)	(0.368)	(0.344)
Term Spread	-0.456	-0.825***	0.340	-0.200
	(0.369)	(0.268)	(0.327)	(0.280)
S&P 500 Return	49.95***	46.90**	30.32*	71.87**
	(16.00)	(22.92)	(17.55)	(28.53)
Unemployment	0.0884	0.277	-0.687**	-0.338
	(0.302)	(0.315)	(0.255)	(0.276)
Consumer Sentiment	-0.00624	-0.0252	-0.0364*	-0.0122
	(0.0145)	(0.0277)	(0.0188)	(0.0224)
LEI Growth	0.404	0.187	0.168	0.482*
	(0.319)	(0.277)	(0.273)	(0.268)
Log EPU	-0.436*	-0.0732	-0.321*	-0.213
	(0.224)	(0.205)	(0.171)	(0.138)
IPO Count	-0.0258**	-0.0120	-0.00674	3.72e-05
	(0.0112)	(0.0146)	(0.0140)	(0.00962)
IPO Return	0.00564	0.00317	0.00702**	-0.00118
	(0.00364)	(0.00329)	(0.00273)	(0.00414)
Constant	3.044	2.856	7.392***	3.775
	(2.767)	(4.271)	(2.297)	(3.065)
Observations	49	49	49	49

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Regression of EPU on Deal Count at various horizons. The full macroeconomic and financial control set are included throughout, all lagged one month. Standard errors are Newey-West.

Table 10:

VARIABLES	(1) Pooled OLS	(2) Industry FE	(3) Ind. FE (Level)	(4) Forward Vol	(5) Past vs Future
Industry Volatility 1M Prior			-0.141**		-0.188**
			(0.0629)		(0.0706)
Industry Volatility 6M Ahead				-0.0464	-0.0313
				(0.0847)	(0.0881)
Δ Industry Volatility 3M Prior	0.0558	0.0531			
	(0.0411)	(0.0385)			
Other Industry Volatility	0.0561	0.0590	0.104	0.110	0.163
	(0.129)	(0.122)	(0.136)	(0.149)	(0.145)
Log EPU	-0.0740	-0.138	-0.213	-0.318	-0.230
	(0.175)	(0.198)	(0.211)	(0.261)	(0.258)
Credit Spread	-0.289	-0.312	0.256	0.292	0.356
	(0.210)	(0.215)	(0.232)	(0.267)	(0.276)
Unemployment	0.00342	0.0222	0.0145	0.0194	0.0156
	(0.0161)	(0.0187)	(0.0140)	(0.0142)	(0.0154)
Industry Returns	-0.0334	-0.0700	-0.0814	-0.0899	-0.171
	(0.189)	(0.196)	(0.166)	(0.164)	(0.173)
Constant	0.578	0.795	0.702	1.135	0.676
	(0.872)	(0.982)	(0.860)	(1.097)	(1.076)
Observations	635	635	786	663	663
R-squared	0.009	0.012	0.011	0.019	0.023
Number of industry_id		11	11	10	10

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: This table shows OLS regression estimates of log industry check size on several industry volatility and macroeconomic controls. Column 1 shows pooled OLS estimates; column 2 adds industry fixed effects with industry volatility change; column 3 uses industry volatility fixed effects with industry volatility level; column 4 replaces lagged volatility with a six-month forward measure to test anticipation; and column 5 includes both lagged and forward volatility to distinguish past from future dynamics. Standard errors are robust and clustered at the industry level.

Table 11:

VARIABLES	(1) Aggregate EPU	(2) Industry Vol	(3) Both
Lag Log EPU	-0.313		-0.223
	(0.174)		(0.219)
Industry Volatility 1M Prior		-0.172**	-0.125*
		(0.0715)	(0.0657)
Other Industry Volatility	0.0451	0.0941	0.115
	(0.126)	(0.116)	(0.130)
Credit Spread	0.274	0.234	0.242
	(0.223)	(0.218)	(0.223)
Unemployment	0.00736	0.00311	0.0141
	(0.0198)	(0.0129)	(0.0138)
Constant	1.249	-0.243	0.761
	(0.722)	(0.144)	(0.907)
Observations	1,002	786	786
R-squared	0.010	0.008	0.011
Number of industry_id	11	11	11

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: This table presents a horse-race regression comparing the predictive power of aggregate EPU and industry-level volatility for changes in log check size. Column 1 includes only lagged EPU, column 2 includes only lagged industry volatility, and column 3 includes both. All regressions include industry fixed effects and macroeconomic controls. Standard errors are clustered at the industry level.

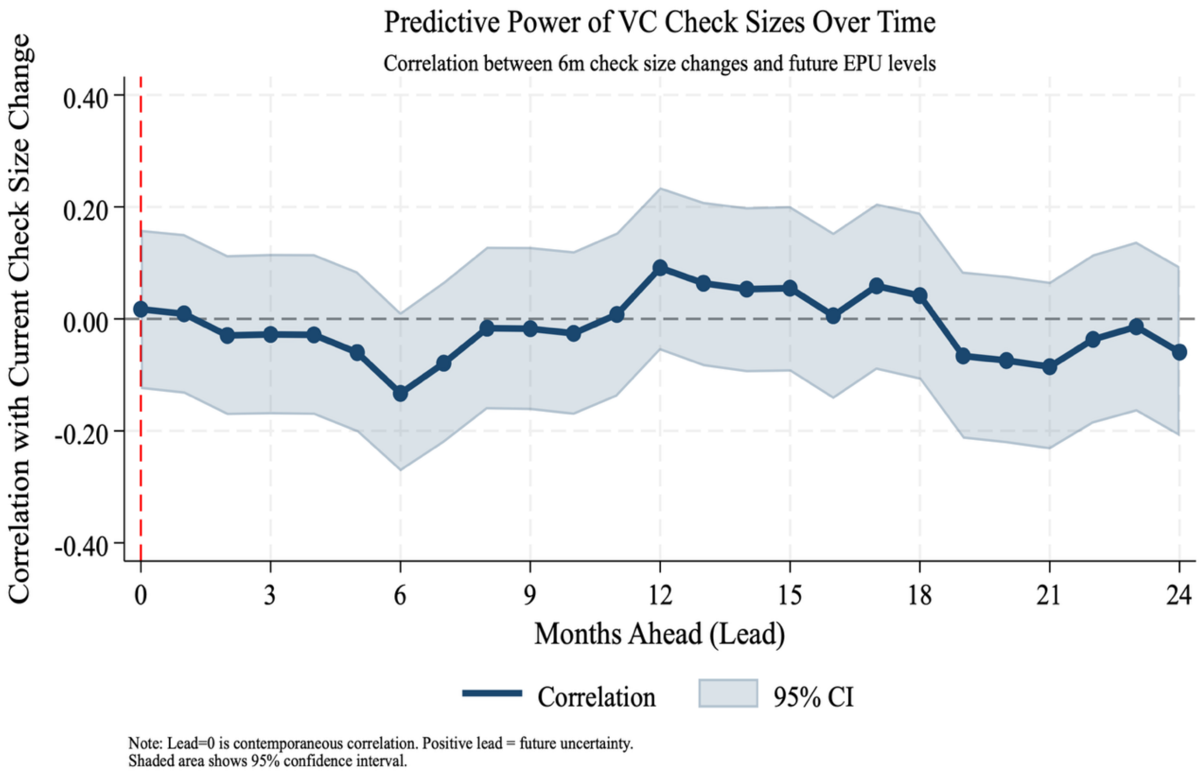
Table 12:

VARIABLES	(1) Baseline	(2) Past Vol	(3) Current Vol	(4) Forward Vol
Forward Industry Vol 6M				0.155
				(0.129)
Forward Vol x Tangibility				-1.300**
				(0.535)
Industry Volatility			0.00996	
			(0.278)	
Current Vol x Tangibility			0.836	
			(1.004)	
Lagged Industry Vol	-0.107	-0.162		
	(0.0636)	(0.124)		
Lagged Vol x Tangibility		0.347		
		(0.988)		
Other Industry Volatility	0.157	0.159	-0.00312	0.165
	(0.144)	(0.145)	(0.325)	(0.157)
Last Month EPU	-0.284	-0.286	-0.351	-0.408
	(0.236)	(0.236)	(0.219)	(0.284)
Credit Spread	0.191	0.191	0.153	0.246
	(0.251)	(0.251)	(0.251)	(0.284)
Unemployment	0.0199	0.0195	0.0206	0.0270
	(0.0144)	(0.0143)	(0.0128)	(0.0153)
Industry Returns	-0.0539	-0.0518	0.00866	-0.0902
	(0.174)	(0.178)	(0.186)	(0.172)
Constant	1.087	1.098	1.432	1.587
	(0.962)	(0.965)	(0.904)	(1.171)
Observations	693	693	693	601
R-squared	0.012	0.012	0.013	0.026
Number of Industries	9	9	9	8

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

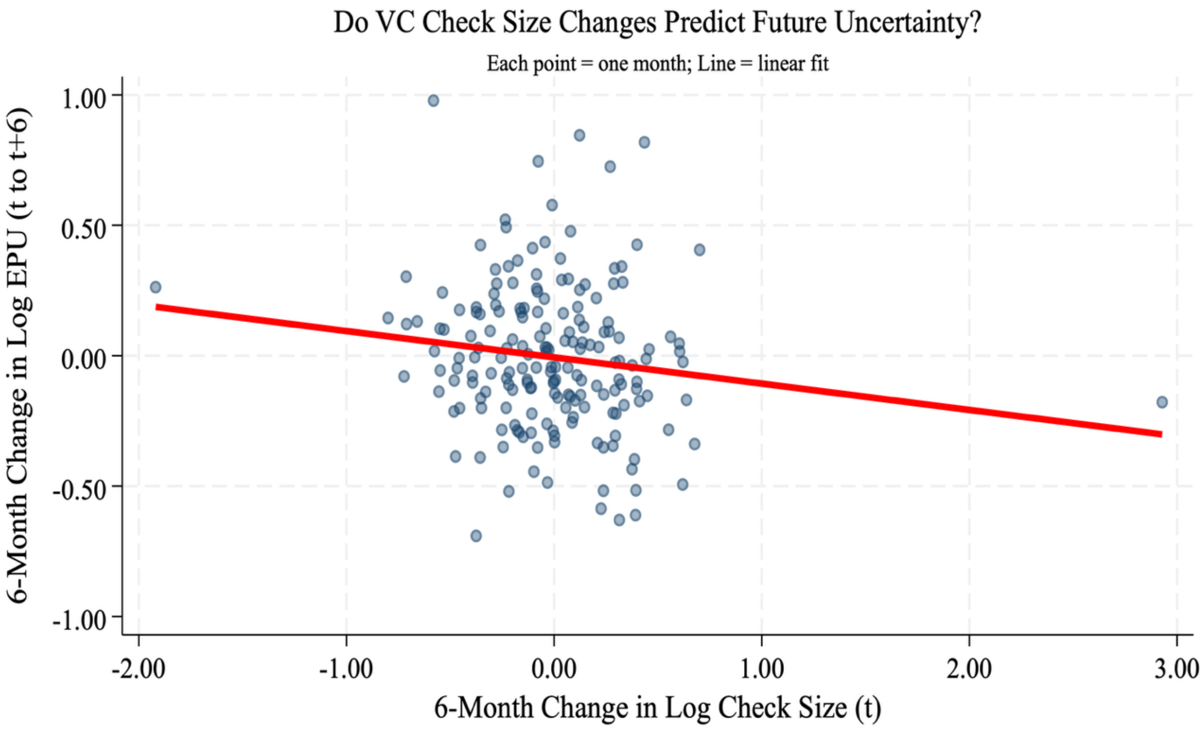
Note: Regression of 6 month lagged log change in check sizes on past, present, and future volatility and industry tangibility interactions. Column 1 replicates the baseline industry volatility result, column 2 adds an interaction between lagged volatility and mean industry tangibility, column 3 repeats this using contemporaneous volatility, and column 4 uses six-month forward volatility to test anticipatory behavior. Standard errors are clustered at the industry level.

Figure 1:



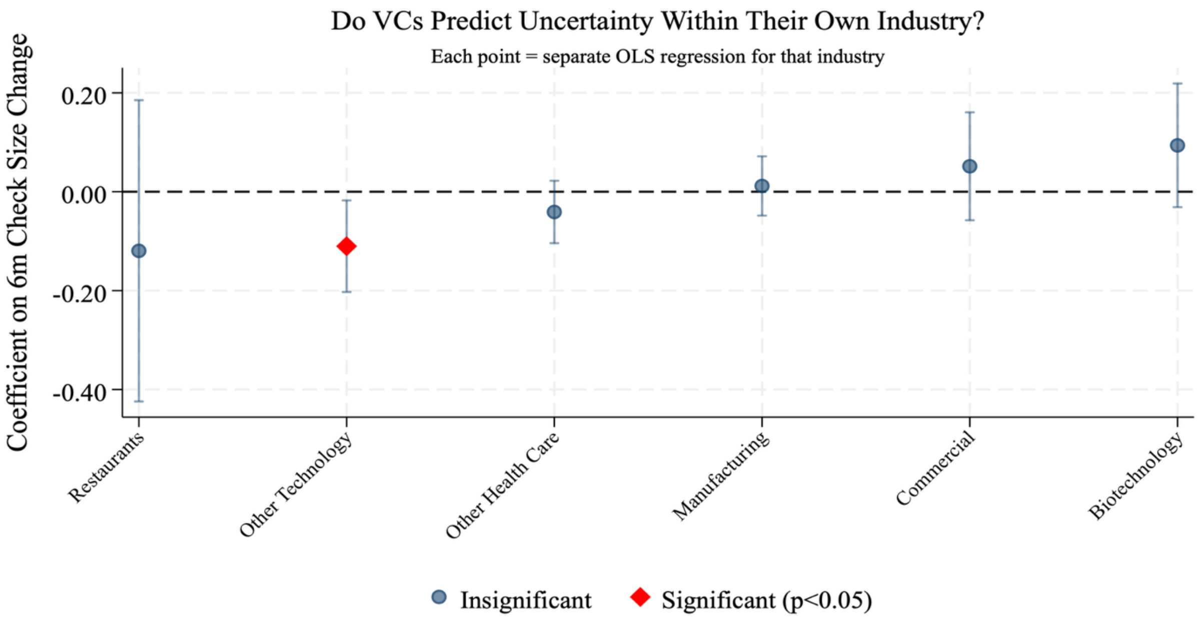
Predictive Power of VC Check Sizes Over Time
Correlation between 6m check size changes and future EPU levels
Correlation with Current Check Size Change
0.40
0.20
0.00
-0.20
-0.40
0
3
6
9
12
15
18
21
24
Months Ahead (Lead)
Correlation
95% CI
Note: Lead=0 is contemporaneous correlation. Positive lead = future uncertainty.
Shaded area shows 95% confidence interval.

Figure 2:



Note: Positive slope suggests check size increases predict rising uncertainty.
Negative slope suggests check size decreases predict rising uncertainty (flight to safety).

Figure 3:


Do VCs Predict Uncertainty Within Their Own Industry?
Each point = separate OLS regression for that industry
Coefficient on 6m Check Size Change
0.20
0.00
-0.20
-0.40
Restaurants
Other Technology
Other Health Care
Manufacturing
Commercial
Biotechnology
Insignificant
Significant (p<0.05)

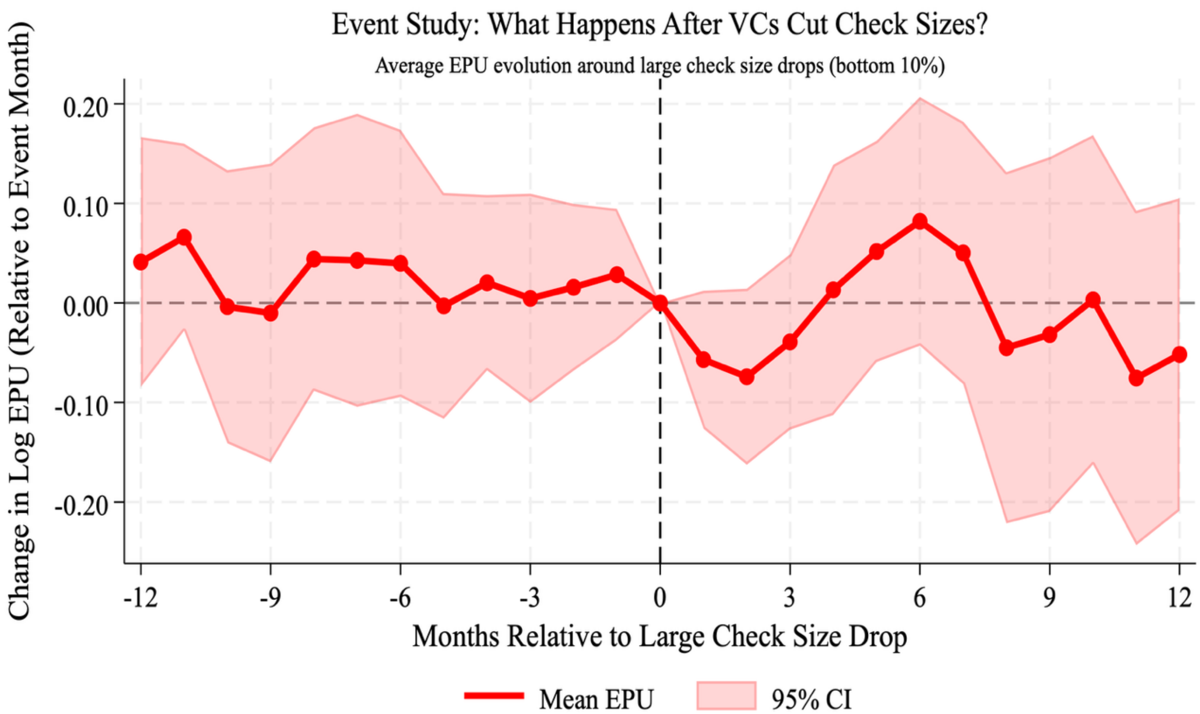
Appendix Table I:

VARIABLES	(1) 1m CS	(2) 3m CS	(3) 9m CS	(4) 12m CS
Δ Log Check Size 12M				0.00826
				(0.139)
Δ Log Check Size 9M			-3.91e-05	
			(0.114)	
Δ Log Check Size 3M		-0.0229		
		(0.126)		
Δ Log Check Size 1M	-0.141			
	(0.118)			
VIX	-0.0124	-0.0114	-0.0116	-0.0118
	(0.0167)	(0.0160)	(0.0160)	(0.0178)
Credit Spread	-0.591	-0.568	-0.562	-0.558
	(0.468)	(0.465)	(0.475)	(0.510)
Term Spread	-0.769***	-0.807***	-0.807***	-0.811***
	(0.274)	(0.285)	(0.270)	(0.287)
S&P 500 Return	43.67*	39.14**	38.57*	38.44*
	(22.11)	(17.13)	(19.12)	(19.01)
Unemployment	0.164	0.231	0.231	0.235
	(0.357)	(0.363)	(0.355)	(0.376)
Consumer Sentiment	-0.0381	-0.0316	-0.0315	-0.0310
	(0.0317)	(0.0324)	(0.0316)	(0.0340)
LEI Growth	0.302	0.288	0.289	0.282
	(0.259)	(0.283)	(0.325)	(0.303)
Log EPU	-0.0616	-0.0259	-0.0284	-0.0242
	(0.220)	(0.233)	(0.243)	(0.252)
IPO Count	-0.0140	-0.0131	-0.0134	-0.0133
	(0.0136)	(0.0148)	(0.0146)	(0.0145)
IPO Return	0.00259	0.00257	0.00249	0.00243
	(0.00314)	(0.00321)	(0.00308)	(0.00323)
Constant	4.606	3.517	3.522	3.438
	(4.958)	(4.941)	(4.907)	(5.318)
Observations	49	49	49	49

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: This is a regression of log change in 6-month forward EPU on various lagged changes in log check size. Each column uses a different horizon for the check size change regressor: 1-month (column 1), 3-month (column 2), 9-month (column 3), and 12-month (column 4). Controls include lagged VIX, credit spread, term spread, S&P 500 return, unemployment, consumer sentiment, LEI growth, log EPU, IPO count, and IPO return. These are all lagged one month. Standard errors are Newey West.

Appendix Figure I:



Note: t=0 is month of large check size drop. Shaded area shows 95% confidence interval.
Pattern shows whether uncertainty rises after VCs pull back.

Appendix Figure II: