The Finance Uncertainty Multiplier*

Iván Alfaro† Nicholas Bloom‡ Xiaoji Lin§

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Abstract

We show how real and financial frictions amplify, prolong and propagate the impact of uncertainty shocks. We first use a novel instrumentation strategy to address endogeneity in estimating the impact of uncertainty, by exploiting differential firm exposure to exchange rate, policy, treasury, and energy price volatility in a panel of US firms. Furthermore, using common proxies for financial constraints, we show that ex-ante financially constrained firms cut their investment more than unconstrained firms following an uncertainty shock. We then build a model with real and financial frictions. We show that adding financial frictions: i) *amplifies* uncertainty shocks by doubling their impact on output; ii) increases *persistence* by doubling the duration of the drop; and iii) *propagates* uncertainty shocks by spreading their impact onto financial variables. These results highlight why in periods of greater financial frictions uncertainty can be particularly damaging.

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†Department of Finance, BI Norwegian Business School, Nydalsveien 37, N-0484 Oslo, Norway. e-mail: ivan.alfaro@bi.no

‡Economics Department, Stanford University, 579 Serra Mall, Stanford CA 94305, email:nbloom@stanford.edu

§Finance Department, Carlson School of Management, University of Minnesota, 321 19th Ave S, Minneapolis, MN 55455. e-mail:xlin6@umn.edu

1 Introduction

This paper studies the interactions between uncertainty shocks and financial frictions both empirically and theoretically. Uncertainty shocks have been argued to play a significant role in explaining the sharp drops in output during the recent financial crisis (e.g. Blanchard (2009)). However, a big challenge to the class of models on uncertainty is that they have difficulty in generating large and persistent responses resembling the slow recovery after the Great Recession. We show that adding financial frictions goes a long way in amplifying the impact of uncertainty shocks, in particular producing a larger recession and a slower recovery. Furthermore, adding financial frictions is also crucial to propagate uncertainty shocks from real into financial outcomes of the economy.

We start off by examining the response to uncertainty shocks of firms' real and financial outcomes of US publicly-listed firms, including tangible and intangible investment, employment, sales, cash, and equity payouts. In particular, taking concerns over endogeneity seriously in estimating the effects of uncertainty[1], we propose a novel instrumentation strategy for uncertainty that exploits differential industry-level exposure to exchange rate, factor price, treasury, and policy uncertainty. Our identification strategy works well in delivering strong first-stage F-statistics and passing the Hansen over-identification tests. We find that higher uncertainty reduces investment (in tangible and intangible capital), hiring and sales growth, while also leading firms to more cautiously manage their financial polices by increasing cash holdings and cutting debt and dividends. Importantly, classifying firms into broad groups of *ex-ante* financially constrained and unconstrained firms, we show that investment of constrained firms responds more intensively to uncertainty shocks than unconstrained firms. Finally, we show how variations in financial conditions can lead to large fluctuations in the aggregate sensitivity of investment to uncertainty - in particular, during the financial crisis of 2008-09 the tighter financial conditions roughly tripled the impact of the higher uncertainty.

[1]See, for example, Nieuwerburgh and Veldkamp (2006), Bachmann and Moscarini (2012), Pastor and Veronesi (2012), Orlik and Veldkamp (2015), Berger, Dew-Becker, and Giglio (2016), and Falgelbaum, Schaal, and Taschereau-Dumouchel (2016), for models and empirics on reverse causality with uncertainty and growth.

To understand the driving forces for the empirical findings we build a heterogeneous firms dynamic model with two key extensions. First, real and financial frictions: on the real side investment incurs a fixed cost,[2] and on the financing side raising external funds involves costs[3] so that firms have to manage liquidity by saving in cash[4]. Second, uncertainty and financing costs are both stochastic, with large shocks. The model is estimated by SMM and then simulated as a panel of heterogeneous firms. We show three key results.

First, an *amplification* effect. Adding financial frictions to the classical model of stochastic-volatility shocks - as in Dixit and Pindyck (1994), Abel and Eberly (1996) or Bloom (2009) - roughly doubles the negative impact of uncertainty shocks on investment and hiring. In our simulation, an uncertainty shock with real *and* financial frictions leads to a peak drop in output of 3.6%, but with *only* real frictions a drop of 1.7%. This happens despite these financial frictions - which we estimate empirically - being small in magnitude (paid realized financial costs average about 20% of paid real adjustment costs). Hence, even small financial adjustment costs generate large amplification effects. The intuition is that introducing financial frictions prevents firms costlessly buffering uncertainty shocks via financial channels. And since Ss bands are extremely sensitive to adjustment costs around zero[5], even small financial frictions can have a major impact.

Furthermore, we show that uncertainty shocks and financial shocks have an almost additive impact on output. In our simulations, uncertainty shocks *or* financial shocks in models with real *and* financial frictions each individually reduce output by 3.6% and 3.2% respectively, but jointly reduce output by 5.3%. We summarize these results below. The table reports the peak drop in aggregate output in our calibrated model with only real frictions and an uncertainty shock is 1.7% (top left box). Adding financial frictions multiplies the impact of

[2]See, for example, Bertola and Caballero (1990), Davis and Haltiwanger (1992), Dixit and Pindyck (1994), Caballero, Engel, and Haltiwanger (1995), Abel and Eberly (1996), Cooper and Haltiwanger (2006), etc.

[3]See, for example, Moyen (2004), Hennessy and Whited (2005), Hennessy and Whited (2007), Bolton, Chen, and Wang (2011) etc.

[4]See, for example, Froot, Scharfstein, and Stein (1993), Bolton, Chen, and Wang (2013), Eisfeldt and Muir (2016), etc.

[5]Dixit (1993) Dixit (1989) and Abel and Eberly (1996) all show that (in continous time models) the derivative of distance between the Ss bands wrt adjustment costs is infinite around zero transactions costs. So even very small adjustment costs can have very large impacts on firm behavior.

an uncertainty shock to 3.6% (bottom left box). Finally, adding a financial shock (as well as an uncertainty shock) increases the impact further, yielding a drop in output of 5.3% (bottom right). So collectively going from the classic uncertainty model to one with financial frictions and simultaneous financial shocks roughly triples the impact of uncertainty shocks, and can help explain why uncertainty shocks during periods like 2007-2009 were associated with large drops in output.

Key results on output in simulation

	Uncertainty shock	Uncertainty + financial shocks
Real frictions	−1.7%	*n/a*
Real+financial frictions	−3.6%	−5.3%

Notes: Results from simulations of 30,000 firms in the calibrated model (see section 5.5).

Our second key result is a *persistence* effect. Adding financial frictions to the standard investment-uncertainty models roughly doubles the duration of drops. In our model with only real adjustment costs an uncertainty shock causes labor, capital and output to drop for 1-2 periods before recovering, while adding financial frictions leads to a 3 period drop for all of them. The intuition is that after an uncertainty shock firms want to build up a cautionary cash balance, impeding their investment rebound.

Our third key result is a *propagation* effect. Financial frictions spread the impact of uncertainty shocks onto financial variables, an important result that the classical model with only real frictions fails to generate. In particular, we show that alongside the negative impact of uncertainty and financial shocks on investment and employment, the model also predicts these shocks will lead firms to accumulate cash and reduce debt and equity payouts, as higher uncertainty causes firms to take a more cautious financial position. As Figure 1 shows this is consistent with macro-data. It plots the quarterly VIX index - a common proxy for uncertainty - alongside aggregate real and financial variables. The top two panels show that times of high uncertainty (VIX) are associated with periods of low investment and employment growth. The middle two panels show that cash holding is positively associated with the VIX, while

dividend payout and equity repurchase are negatively related to the VIX. The bottom panel also considers debt and shows that the total debt (the sum of the short-term and long-term debt) growth is negatively related with the VIX.

The additional complexity required to model: (a) real and financial frictions, and (b) uncertainty and financial shocks, required us to make some simplifying assumptions. First, we ignore labor adjustment costs - including these would likely increase the impact of uncertainty shocks, since labor accounts for 2/3 of the cost share in our model. Indeed, as a partial test of this we increase the capital share to 1 and show a far larger impact of uncertainty shocks. Second, we ignore general equilibrium (GE) effects - including these would likely reduce the impact of uncertainty shocks by allowing for offsetting price effects. As a partial response to this we also run a pseudo-GE robustness test where we allow interest rates, prices (of output and capital) and real wages to move after uncertainty shocks following typical changes observed in the data, and find the impact of an uncertainty shock is about 20% smaller[6].

Related literature Our paper builds on three broad literatures. First, the uncertainty literature studying the interaction of uncertainty and adjustment costs for investment and employment.[7] This emphasizes the "real options" effects of uncertainty, which describes how firms act more cautiously on their real activities in the presence of uncertainty and real adjustment costs. We contribute to this literature empirically by providing *causal* empirical support to identify the impact of uncertainty on investment and employment by using a novel instrumentation

[6]One reason from the limited impact of GE is that wages and real interest rates do not move substantially over the cycle (e.g. King and Rebelo (1999)), and second increased uncertainty widens the Ss bands so that the economy is less responsive to price changes (e.g. Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018)).

[7]Classic papers on uncertainty and growth included Bernanke (1983), Romer (1990), Ramey and Ramey (1995), Leahy and Whited (1996), Guiso and Parigi (1999), Bloom (2009), Bachmann and Bayer (2013), Fernandez-Villaverde, Quintana, Rubio-Ramirez, and Uribe (2011), Fernandez-Villaverde, Guerron-Quintana, Kuester, and Rubio-Ramirez (2015), and Christiano, Motto, and Rostagno (2014). One more closely related paper that studies the causal impact of uncertainty shocks using a related exposure approach is Stein and Stone (2013). Several other papers also look at uncertainty shocks - for example, Bansal and Yaron (2004) and Segal, Shaliastovich, and Yaron (2015) look at the consumption and financial implications of uncertainty, Handley and Limao (2012) look at uncertainty and trade, Ilut and Schneider (2014) model ambiguity aversion as an alternative to stochastic volatility, and Basu and Bundick (2017) examine uncertainty shocks in a sticky-price Keynesian model, and Berger, Dew-Becker, and Giglio (2016) study news vs uncertainty. A related literature on disaster shocks - for example, Rietz (1988), Barro (2006), and Gourio (2012) - is also connected to this paper, in that disasters can be interpreted as periods of combined uncertainty and financial shocks, and indeed can lead to uncertainty through belief updating (e.g. Orlik and Veldkamp (2015)).

strategy of exposure to energy, currency, treasury, and policy uncertainty to identify causal effects.

Second, the finance literature on firms' financial management of liquidity. The notion of liquidity management goes back at least to John Maynard Keynes (1936) who argued that precautionary cash saving and financing constraints are closely linked if financial markets are imperfect.[8] This literature highlights how firms will hoard cash in the presence of uncertainty and *financial* adjustment costs - i.e., costs of issuing debt and/or equity. This is a "cash options" equivalent to a "real options" effect (the idea that having cash in the firm preserves the option to issue debt or equity in the future). We extend this literature by showing how the combination of "real options" and "cash options" from real and financial adjustment costs respectively combine together to multiply the impact of uncertainty shocks on firms real (investment and hiring) and financial (cash and external financing) behavior.[9]

Finally, our paper is also closely related to the recent literature on financial frictions and business cycles.[10] We build on this literature to argue it is not a choice *between* uncertainty shocks and financial shocks as to which drives recessions, but instead these shocks *amplify* each other. So they should not be considered individually, rather jointly. Related work that links uncertainty and financial frictions includes the following. Gilchrist, Sim, and Zakrajsek (2014) study the relationships between uncertainty, investment and credit spreads, and show

[8] Meltzer (1963), Miller and Orr (1966), and Baumol (1970) are earlier examples emphasizing the transaction motive of firms to hold cash. The recent development in the finance literature on liquidity managemnet and financial constraints include the theoretical work by Froot, Scharfstein, and Stein (1993), Holmstrom and Tirole (1998), Riddick and Whited (2009), Bolton, Chen, and Wang (2011), Bolton, Wang, and Yang (Forthcoming), etc., and the empirical work by Almeida, Campello, and Weisbach (2005), Bates, Kahle, and Stulz (2009), Pinkowitz, Stulz, and Williamson (2013), etc., Almeida, Campello, Cunha, and Weisbach (2014) provides a survey of the literature.

[9] There is a large literature, for example, Rajan and Zingales (1995), Gomes (2001), Welch (2004), Hennessy and Whited (2005), DeAngelo, DeAngelo, and Whited (2011), Rampini and Viswanathan (2013), Chen, Wang, and Zhou (2014), and Chen (2016) that study the impact of various frictions on firms' financing policies.

[10] For example, Sharpe (1994) shows that financial leverage propagates the impact of demand shocks on firms' employment over business cycles; Alessandri and Mumtaz (2018) and Lhuissier and Tripier (2016) show in VAR estimates a strong interaction effect of financial constraints on uncertainty. More generally, Gilchrist and Zakrajsek (2012), Jermann and Quadrini (2012), show that financial frictions are important to explain the aggregate fluctuations for the recent financial crisis. Caggiano, Castelnuovo, and Figueres (2017) show that uncertainty shocks have a bigger impact during recessions. Giroud and Mueller (2017) show that establishments with higher financial leverage cut employment more in response to negative local consumer demand shocks.

that financial frictions magnify the effects of uncertainty through changes in credit spreads. Christiano, Motto, and Rostagno (2014) imbed agency problems associated with financial intermediation as in Bernanke, Gertler, and Gilchrist (1999) into a monetary dynamic general equilibrium model; they find volatility shocks are important in driving the business cycle. Arellano, Bai, and Kehoe (2019) build a DSGE model with frictions in labor and financial markets. They show that uncertainty shocks lead to higher default risk and credit spreads, which cause firms to further cut employees. Ottonello and Winberry (2016) investigate the relationship between financial frictions and firm heterogeneity and the impact of monetary policy on firms' investment. Although we share with Gilchrist, Sim, and Zakrajsek (2014), Christiano, Motto, and Rostagno (2014) and Arellano, Bai, and Kehoe (2019) the idea that financial frictions amplify the impact of uncertainty shocks, our work differs in three important ways. First, we develop a micro-data identification strategy to estimate the *causal* impact of uncertainty and financial shocks on firms. The set of variables examined in our paper that causally respond to uncertainty shocks covers both real and financial variables. Addressing endogeneity is important given potential bias and inconsistency in estimating the effects of uncertainty when using metrics based on financial measures like stock-returns[11]. Second, we use common proxies for financial constraints proposed in the finance literature to provide empirical evidence for the amplification prediction of the model, finding that *ex-ante* financially constrained firms cut investment substantially more than unconstrained firms in response to uncertainty shocks. Third, we include cash in our model, allowing firms an additional cash balance dimension to respond to uncertainty. Modeling cash is important given that cash holdings have increased in the US and Europe, with rising uncertainty one suggested reason[12].

The rest of the paper is laid out as follows. Section 2 describes the instrumentation strategy

[11]The typical prior approach in this literature to instrumentation - for example Leahy and Whited (1996), Bloom, Bond, and Reenen (2007) and Gilchrist, Sim, and Zakrajsek (2014) - is to use lagged values of uncertainty as instruments in OLS regressions. We propose instruments that caputure exogenous variation in uncertainty in a 2SLS framework.

[12]See Pinkowitz, Stulz, and Williamson (2013), Pinkowitz, Stulz, and Williamson (2016), and Chen, Karabarbounis, and Neiman (2017)

and data. Section 3 presents the empirical findings on the effects of uncertainty shocks on both real and financial activity of firms. In section 4 we write down the model. Section 5 presents the main quantitative results of the model. Section 6 concludes.

2 Data, instruments, and addressing endogeneity

This section discusses the data sources used for the empirical analysis. It also details the construction of the instruments used in addressing potential endogeneity concerns in measuring the effects of firm-level uncertainty shocks.[13]

2.1 Data

Stock returns are from CRSP and annual accounting variables are from Compustat. The sample period is from January 1963 through December 2016. Financial, utilities and public sector firms are excluded (i.e., SIC between 6000 and 6999, 4900 and 4999, and equal to or greater than 9000). Compustat variables are at the annual frequency. Our main firm-level empirical tests regress changes in real and financial variables on 12-month lagged changes in uncertainty (i.e., lagged uncertainty shocks), where the lag is both to reduce concerns about contemporaneous confounding endogeneity and because of natural time to build delays. Moreover, our main tests include both firm and time (calendar year) fixed effects. The regressions of changes in outcomes on lagged annual changes in uncertainty restricts our sample to firms with at least 3 consecutive non-missing data values. The firm fixed effect further restricts this to firms with at least 4 non-missing data values (as it eliminates singletons). To ensure that the changes are indeed annual, we require a 12 month distance between fiscal-year end dates of accounting reports from one year to the next. We also drop any firm-year observations having zero or negative employment, total assets, and/or sales.

In measuring firm-level uncertainty we employ both *realized* annual volatility from CRSP

[13] A full replication file for data construction and regressions is available on https://people.stanford.edu/nbloom/.

stock returns and *option-implied* volatility from OptionMetrics. Realized volatility is the standard-deviation of daily cum-dividend stock returns over the course of each firm's fiscal year (which typically spans roughly 252 trading days).[14] For implied volatility we use the 252-day average of daily implied volatility values from OptionMetrics. Data from OptionMetrics is available starting January 1996. Our daily implied volatility data corresponds to at-the-money 365-day forward call options. Additional information about OptionMetrics, Compustat, and CRSP data is provided in Appendix (A).

For changes in variables we define growth following Davis and Haltiwanger (1992), where for any variable x_t this is $\Delta x_t = (x_t - x_{t-1})/(\frac{1}{2}x_t + \frac{1}{2}x_{t-1})$, which for positive values of x_t and x_{t-1} yields growth rates bounded between -2 and 2. The only exceptions are CRSP stock returns (measured as the compounded fiscal-year return of daily stock returns RET from CRSP) and capital formation. For the latter, investment rate is defined as $\frac{I_{i,t}}{K_{i,t-1}}$, where $K_{i,t-1}$ is net property plant and equipment at the end of fiscal year $t-1$, and $I_{i,t}$ is the flow of capital expenditures ($CAPX$ from Compustat) over the course of fiscal year t. After applying all filters to the data, all changes, ratios, and levels of variables are then winsorized every fiscal year at the 1 and 99 percentiles .

Our main tests include standard controls used in the literature on both real investment and capital structure. In particular, in addition to controlling for the effect on investment of first-moment variables, i.e., the lagged level of Tobin's Q and the lagged stock return of each firm, we follow the lagged timing and controls in Leary and Roberts (2014) in all of our main multivariate tests, specifically controlling for the lagged levels of book leverage, return on assets, firm tangibility, and log sales. The Appendix (A) details the construction of these variables.

[14] We drop observations of firms with less than 200 daily CRSP returns in a given fiscal year. Our sample uses securities appearing on CRSP for firms listed in major US stock exchanges (EXCHCD codes 1,2, and 3 for NYSE, AMEX and the Nasdaq Stock Market (SM)) and equity shares listed as ordinary common shares (SHRCD 10 or 11).

2.2 Identification strategy

Our identification strategy exploits firms' differential exposure to aggregate volatility shocks in energy, currency, policy, and treasuries to identify exogenous changes in firm-level volatility that are orthogonal to the endogenous components driving firm-level volatility shocks. For example, to identify exogenous variation using oil, the idea is that some firms are positively sensitive to oil prices (e.g. mining and oil exploration firms), some are negatively sensitive (e.g. airlines and energy-intensive manufacturing firms), while others are neutral (e.g. business service firms). As such, these firms have a different exposure to the first moment (oil price levels) - which is positive, negative and zero respectively - compared to the second moment (oil price uncertainty), which is positive, positive and zero respectively. So we can control for oil price levels exposure while separately identifying the impact oil price uncertainty exposure. We extend this idea to 10 sources of uncertainty - oil prices, 7 currencies, interest rates and policy - to generate 10 instruments to generate broad movements in uncertainty.

Estimation of sensitivities The sensitivities to energy, currencies, treasuries, and policy are estimated at the industry level as the factor loadings of a regression of a firm's daily stock return on the price growth of energy, 7 currencies, return on treasury bonds, and changes in daily policy uncertainty. That is, for firm i in industry j, $sensitivity_i^c = \beta_j^c$ is estimated as follows

$$r_{i,t}^{risk_adj} = \alpha_j + \sum_c \beta_j^c \cdot r_t^c + \epsilon_{i,t} \tag{1}$$

where $r_{i,t}^{risk_adj}$ is the daily risk-adjusted return on firm i, r_t^c is the change in the price of commodity c, and α_j is industry j's intercept. The sensitivities are estimated at the industry level using daily returns of firms that share the same 3-digit Standard Industrial Classification (SIC) code. Estimating the main coefficients of interest, β_j^c, at the SIC 3-digit level (instead of at the firm-level) reduces the role of idiosyncratic noise in firm-level returns, increasing the precision of the estimates. We allow these industry-level sensitivities to be time-varying by estimating them using 10-year rolling windows of daily data.

The risk-adjusted returns $r_{i,t}^{risk_adj}$ in (1) are the residuals from running firm-level time-

series regressions of daily CRSP stock returns on the classical Carhart (1997) four-factor asset pricing model (details in Appendix section A.7). Adjusting firm-level returns for aggregate risk addresses concerns over whether the sensitivities to energy, currencies, treasuries, and policy are capturing exposures to common risk factors (although in practice this makes almost no difference).

The daily independent variables in (1) are the growth in crude-oil prices (which proxies for energy shocks), growth in the exchange rates of 7 widely traded currencies defined as "major" currencies by the Federal Board [15], the return on the US 10-year treasury note [16], and the growth in economic policy uncertainty from Baker, Bloom, and Davis (2016).

Construction of instruments For these 10 aggregate market price shocks (oil, 7 currencies, treasuries, and policy) we multiply the absolute value of their time-varying sensitivities $\mid \beta^c_{j,t-\tau} \mid$ by shocks to their *implied* volatilities $\Delta\sigma^c_t$. This provides 10 instruments for lagged firm-level uncertainty shocks, $\Delta\sigma_{i,t-1}$, as follows:

$$z^c_{i,t-1} = \mid \beta^c_{j,t-\tau} \mid \cdot \Delta\sigma^c_{t-1} \tag{2}$$

For the implied volatilities, σ^c_{t-1}, of oil and the 7 currencies we use the 252-day average of daily 3 month implied volatilities of crude oil futures and currencies from Thomson Reuters Eikon. For 10-year treasuries we use the 252-day average of daily implied volatility for the 10-year US Treasury Note from the Cboe/CBOT (ticker TYVIX), and for economic policy we use the 252-day average of weekday US economic policy uncertainty (EPU) from Baker, Bloom, and Davis (2016).[17]

In constructing the instruments we make two other refinements. First, to address concerns of noisy estimates and multicollinearity in (1) we adjust each sensitivity, β^c_j, by its statistical

[15] See http://www.federalreserve.gov/pubs/bulletin/2005/winter05_index.pdf . These include: the Euro, Canadian Dollar, Japanese Yen, British Pound, Swiss Franc, Australian Dollar, and Swedish Krona. Each of these trade widely in currency markets outside their respective home areas, and (along with the U.S. dollar) are referred to by the Board staff as major currencies.

[16] The treasury return is estimated from the first-order approximation of duration, i.e., by multiplying the first difference of the yield by minus 1.

[17] In contrast to oil, 7 currencies, and 10-year treasuries EPU volatility is only available in realized form, and not option-implied. Nonetheless, our main results are robust to both using only option-implied volatility data for the 9 variables (excluding EPU) and using realized volatility for all variables.

significance within each industry, $\beta_j^{c,weighted} = \omega_j^c \cdot \beta_j^c$. The sensitivity weight $\omega_j^c = \mid t_j^c \mid / \sum^c \mid t_k^c \mid$ is the ratio of the absolute value of the t-statistic of each instrument's sensitivity to the sum of all t-statistics in absolute value of instruments within the industry. This avoids using exposures in the 2SLS first stage that are imprecisely estimated. Second, we lag the weighted sensitivities by three years to ensure all the sensitivity measures pre-date both the outcome variables and lagged controls. This avoids using data for the instruments that overlaps in time with information entering the annual investment rate of firms $\frac{I_{i,t}}{K_{i,t-1}}$ at time t and controls $X_{i,t-1}$ at time $t-1$. [18]

Hence, the final 10 uncertainty instruments for lagged firm-level uncertainty shocks, $\Delta\sigma_{i,t-1}$, are $\mid \beta_{j,t-3}^{c,weighted} \mid \cdot \Delta\sigma_{t-1}^c$. In words, this is the 3-year lagged cross-industry non-directional exposure measure times the lagged change in implied volatility for oil prices, 7 leading currencies, interest rates and policy uncertainty. As discussed below, we show in Appendix section A.10 that results are robust to using unweighted instruments in (2).

In our baseline multivariate specifications we also include two additional sets of controls. First, annual exposure to the returns (rather than volatility) of each instrument. That is, $\beta_{j,t-3}^{c,weighted} \cdot r_{t-1}^c$, which is both directional ($\beta_{j,t-3}^{c,weighted}$ can be positive or negative) and uses the aggregate first-moment r_{t-1}^c (rather than second moment $\Delta\sigma_{t-1}^c$)[19]. These aggregate first moment controls help disentangle the correlated movements in first and second moments - for example, oil prices tend to be more volatile when they are high. Second, we also control for firm-level measures of first moment effects, i.e., Tobin's $Q_{i,t-1}$ and the CRSP stock return of the firm, $r_{i,t-1}$, as well as a set of standard financial controls from Leary and Roberts (2014). In all, the large set of controls in addition to the firm and time fixed effects allows our empirical examination to focus on the effects of 2SLS instrumented firm-level uncertainty shocks, $\widehat{\Delta\sigma_{i,t-1}}^{2SLS}$, above and beyond first moment effects.

[18] See Appedix section A.6 for additional details on the exact timing of instruments and other variables.

[19] For economic policy uncertainty we measure r_t^c as growth from one year to the next in the reciprocal of the 4-quarter average of government expenditures as a share of GDP. For currencies, oil, and treasuries returns r_t^c are the 252-day average of daily returns.

3 Empirical findings

We start by examining how volatility shocks relate to firm-level capital investment rates, followed by other real outcomes -intangible capital investment, employment, and cost of goods sold- and then by financial variables - debt, payout, and cash holdings.[20]

3.1 Investment results

Table 1 examines the effect of uncertainty shocks on capital investment rates. Column 1 presents the univariate OLS regression results of investment rate on lagged annual *realized* stock return volatility growth. The specification includes only firm and time fixed effects and standard errors at clustered (conservatively) at the 3-digit SIC industry (the same level at which factor exposures are estimated). The point estimate in Column 1 of -0.032 is highly significant (t-stat of 20.2), and indicates that the annual investment of firms as a fraction of the lagged capital stock declines by 3.2 percentage points following a doubling in firm-level volatility (roughly a 3.3 standard deviation volatility shock). Relative to the unconditional mean annual investment rate of 24.8% (see descriptive statistics in Table D.9), this is a decline of 12.9% per year. Column 4 presents the results of a similar OLS univariate regression but using option-*implied* volatility shocks. The size of the coefficient is almost three times as large while remaining highly significant (estimate -0.089, t-stat -10.570). The larger size associated with option-implied volatility is possibly because it is a less noisy measure of uncertainty, and/or as a forward-looking variable may also be less prone to the endogeneity concerns in realized returns volatility.[21]

These results indicate that uncertainty shocks correlate negatively with real firm investment decisions. However, as explained in section A.9, inferences from OLS results are likely to suffer from endogeneity bias. So in columns 2 and 3 we instrument lagged *realized*

[20] See https://nbloom.people.stanford.edu/research for the Stata code to replicate all results.

[21] We reestimate both specifications in columns (1) and (4) on a common sample of 17,481 observations in table (D.14) and find similar realized and implied volatility coefficients are -0.033 and -0.080, both significant at the 1%.

volatility shocks while columns 5 and 6 instrument lagged *implied* volatility shocks. Columns 2 and 5 are univariate while 3 and 6 are multivariate with a full set of controls at both the firm- and aggregate-levels. In all cases we find that uncertainty shocks lead to significant drops in firm-level investment, with significance at the 1% in all 6 column specifications. Moreover, the instrumentation strategy seems to work well, as seen by the first-stage F-tests that look reasonable with values of around 10 to 15, and a Sargan over-identification test that does not reject the validity of the instruments (full 2SLS first stage results are discussed and presented in Appendix section A.8).

In summary, Table 1 provides *causal* support that increases in uncertainty lead to future reductions in capital investment rates of US publicly listed firms. In terms of magnitudes our preferred results (columns (3) and (6)) imply that a *two-standard* deviation increase in realized and implied volatility shocks reduce the rate of investment between 2.1 to 4.0 percentage points, respectively. These are small compared to the unconditional mean of firm-level investment of 24.8% (see Table D.9), but large in comparison to the 3.32 percentage point total drop in aggregate investment during recessions.[22]

3.2 Intangible capital, employment, and cost of goods sold

Table 2 examines the implications of uncertainty shocks on the growth of other *real* outcomes. In particular, Panel A examines investment in intangible capital (as measured by expenditure on general and administration items plus R&D, which extends the approach of Eisfeldt and Papanikolaou (2013)), Panel B examines employment, Panel C examines the cost of goods sold, and Panel D examines sales. In each panel we present the same 6 specification results presented for investment in Table 1, but to preserve space we don't show the point coefficient estimates on controls, and focus only on the estimates on lagged uncertainty shocks.

[22]The average difference in total drop of NIPA gross private domestic investment/GDP ratios from 1947Q1-2018Q4 between NBER-defined recessions and the period just before recessions. In particular, we measure the average difference between the minimum aggregate ratio during recessions and the maximum ratio during the 4-quarter period preceding a recession. We use a 4-quarter preceding window to measure the max as it is the average length of the 11 NBER recessions during 1947Q1-2018Q4.

Regardless of which of the 24 specification we look at, the signs on each of the uncertainty coefficients is negative, confirming the negative relationship between real outcomes and uncertainty. Moreover, in terms of significance, regardless of whether we instrument realized or option-implied uncertainty shocks, in columns (3) and (6), we see significant drops in intangible capital investment, cost of goods sold, and sales after higher uncertainty. The response of employment (which is only measured yearly, is not audited, and is often reported with heavy rounding) is negative but not statistically significant in the multivariate 2SLS tests, although other audited inputs measures like the cost of goods sold do show significant negative responses to uncertainty.

Overall, the four panels in Table 2 provide *causal* support for the model in section 4, and confirm that the negative real effects of uncertainty shocks are not limited to capital investment presented in Table 1, but extends to a broader mix of production inputs and outputs. This impact is robust to the presence of extensive controls for first-moment and financial conditions (which are further expanded in robustness checks below), and robust to endogeneity concerns addressed by our instrumentation strategy for uncertainty shocks.

3.3 Financial variables

Table 3 examines the impact of uncertainty shocks on the growth of *financial* variables. In particular, Panel A examines dividend payout, Panel B total debt, and Panel C cash holdings. Regardless of which of the 18 specifications we look at, uncertainty shocks have significant financial effects on publicly listed firms. All point estimates on uncertainty shocks are significant at the 1% (mostly) or 5%. Consistent with the model in section 4, the impact of uncertainty shocks makes firms more cautious - cutting equity payouts and debt while increasing holdings of cash. Panel A indicates that firm's cut their cash dividend payouts following an uncertainty shock. Panel B shows that increases in uncertainty leads firms to reduce their debt, while Panel C shows additional evidence of a precautionary savings channel, as cash holdings strongly increase following high uncertainty shocks. These results are robust

to either OLS or IV estimations, with or without controls, and using realized or implied volatility.

In all, Table 3 provides *causal* support that uncertainty shocks not only have real implications (as seen in Tables 1 and 2) but also strong financial effects on firms. Moreover, the strong 1st stage results highlight that our instrumental strategy based on exchange rate, policy, and factor price volatility also works well for financial variables of US firms.

We also conducted numerous robustness checks on our instrumentation strategy, functional form of uncertainty, and additional controls for credit supply shocks and financial constraints to our baseline 2SLS regressions reported to this point. These extensive robustness checks are discussed in Section A.10 in Appendix.

3.4 Financing frictions and uncertainty shocks

We next examine whether financial frictions amplify the negative real effects of uncertainty shocks by running a series of interactions of *uncertainty shocks* with *financial frictions*. We analyze the amplification effect in two dimensions.

First, we ask whether there is evidence that the investment rate of firms responds more intensively to uncertainty shocks during periods of heightened aggregate financial frictions. We use Moody's aggregate BAA-AAA corporate credit spread from St. Louis Fed as baseline to account for movements in aggregate financial frictions affecting all firms. The annual series is standardized to ease interpretation of coefficients (see data Appendix A). Therefore, we expect that firms cut investment, $\frac{I_{i,t}}{K_{i,t-1}}$, after increased uncertainty shocks, $\Delta\sigma_{i,t-1}$, and this cut is amplified further during periods of high aggregate financial frictions, $\Delta\sigma_{i,t-1} \cdot Credit_Spread_t$, predicting $\beta_1 < 0$ and $\beta_2 < 0$ in:

$$\frac{I_{i,t}}{K_{i,t-1}} = \beta_1 \Delta\sigma_{i,t-1} + \beta_2(\Delta\sigma_{i,t-1} \cdot Credit_Spread_t) + \beta_3 Credit_Spread_t + X_{i,t-1} \cdot \gamma + \delta_i + \phi_t + \varepsilon_{i,t} \tag{3}$$

Column 1 in Table 4 presents these results using our baseline 2SLS realized regression with full set of controls $X_{i,t-1}$, firm δ_i and time ϕ_t fixed effects (i.e., columns (3) in Table 1). Indeed,

firms significantly cut their investment rates in response to uncertainty shocks ($\beta_1 = -0.025$, significant at the 5%) and do so further during high aggregate financial frictions ($\beta_2 = -0.035$, significant at the 1%). Therefore, data on public firms implies a total effect of uncertainty shocks in high financial friction years (i.e., 1 standard deviation increase in the Moody's credit spread) equal to a total drop in investment rate of $\beta_1 + \beta_2 = -0.06$ (significant at the 1%). These coefficients give us an amplification measure for the amplification effect when going from normal aggregate financial frictions to high frictions: $(-0.06/-0.025) = 2.4$).

Second, we ask the stronger question whether such difference in intensity is amplified even further for ex-ante financially constrained firms relative to unconstrained. The idea is that periods of high aggregate financial frictions are precisely when we would expect financially constrained firms to respond more strongly to uncertainty. Thus, by classifying firms into broad ex-ante groups using common proxies for financial constraints, we asses whether the firms that would likely see more binding constraints, respond even more intensively to uncertainty shocks relative to less constrained firms. To test this hypothesis we expand the above interaction specification in (3) and run the following 2SLS triple interaction:

$$\begin{aligned}\frac{I_{i,t}}{K_{i,t-1}} &= \beta_1 \Delta\sigma_{i,t-1} + \beta_2(\Delta\sigma_{i,t-1} \cdot Credit_Spread_t) + \beta_3 Credit_Spread_t \\ &+\beta_4(\Delta\sigma_{i,t-1} \cdot D_{i,t-5}^{fin.constraint}) + \beta_5 D_{i,t-5}^{fin.constraint} + \beta_6(D_{i,t-5}^{fin.constraint} \cdot Credit_Spread_t) \\ &+\beta_7(\Delta\sigma_{i,t-1} \cdot D_{i,t-5}^{fin.constraint} \cdot Credit_Spread_t) \\ &+X_{i,t-1} \cdot \gamma + (X_{i,t-1} \cdot D_{i,t-5}^{fin.constraint}) \cdot \gamma^{fin.constraint} + \delta_i + \phi_t + \varepsilon_{i,t} \qquad (4)\end{aligned}$$

where $D_{i,t-5}^{fin.constraint}$ is a dummy that takes value one for firms classified as ex-ante financially constrained using information in fiscal year $t-5$, zero otherwise. Using a lag of 5 full years to classify firms helps us address potential concerns about endogeneity that might exist in commonly used proxies for financial constraints - which we borrow from the literature and described below. Moreover, the 4 coefficients involving firm uncertainty shocks allow us to examine and formally test the stronger version of the amplification effect. In particular, the total effect of uncertainty shocks for ex-ante *unconstrained* firms during high aggregate frictions is captured by coefficients $\beta_1 + \beta_2$, while the total effect for ex-ante *constrained* firms

is $\beta_1 + \beta_2 + \beta_4 + \beta_7$. Therefore, the difference in these total effects, $\beta_4 + \beta_7$, captures the incremental response of constrained firms in years when their financial constraints likely bind the most.

To classify firms we employ three widely used measures in the finance literature that proxy for firm-level financial constraints (e.g., Panousi and Papanikolaou (2012)). Using each firm's proxy built from information in fiscal year $t-5$, we classify firms every year. In particular, we consider a firm in year t as ex-ante financially constrained if at year $t-5$ its individual financial constraint measure is equal to or above the cross-sectional median constrained firm that year. Firms below the median firm are then considered ex-ante unconstrained in year t. [23]

The financial constraint proxies are: first, an index based on external credit ratings given to firms by Standard and Poor's (S&P) in column (2), here we follow Duchin, Ozbas, and Sensoy (2010) and consider a firm constrained if it has positive debt and no bond rating and unconstrained otherwise (which includes firms with zero debt and no debt rating)[24]; second, the Size and Age index (SA) of Hadlock and Pierce (2010) in column (3); third, the Whited and Wu (2006) in column (4).

Before discussing the results from running (4) in columns (3) (4) and (5) of Table 4 we first run a restricted model that interacts the firm uncertainty shock with the financial constraint dummy based on the S&P credit ratings. In particular:

$$\frac{I_{i,t}}{K_{i,t-1}} = \beta_1 \Delta\sigma_{i,t-1} + \beta_4(\Delta\sigma_{i,t-1} \cdot D^{fin.constraint}_{i,t-5}) + \beta_5 D^{fin.constraint}_{i,t-5} + X_{i,t-1} \cdot \gamma + \delta_i + \phi_t + \varepsilon_{i,t} \quad (5)$$

Column (2) shows that both ex-ante constrained and unconstrained firms significantly cut their investment rates in response to uncertainty shocks ($\beta_1 = -0.033$, significant at the

[23] The use of cutoffs to classify firms into broad groups instead of using the continous firm-level financial constraint measures is also standard (e.g., Panousi and Papanikolaou (2012) and Duchin, Ozbas, and Sensoy (2010)) because firm-level measures are imperfect proxies for financial constraints, yet they largely suceed at broadly capturing differences across constrained and unconstrained groups. We follow Duchin, Ozbas, and Sensoy (2010) in using the median firm each year as cutoff to classify firms, yet our results are robust to dropping firms in the vicinity of the median firm (e.g., +/-5% around the median). Firms in this region are less clear of being unconstrained or constrained, and thus dropping them increases accuracy of firm splits.

[24] For ratings data we use Compustat-Capital IQ's ratings data from WRDS, where ratings dummies are based on variable SPLTICRM (S&P Domestic Long-Term Issuer Credit Rating).

5%), yet there is no significant evidence that in a given average year ex-ante constrained firms respond more intensively to uncertainty than unconstrained firms. This is indicated by the coefficient $\beta_4 = -0.01$, which although negative and implying a 1 percentage point difference in the drop of investment between the two groups, is insignificant. This does not mean, however, that the response of investment between the two groups of firms does not differ in years when their financial constraints are likely binding the most. This is likely to occur precisely in years where the Moody's aggregate credit spread spikes upward - as this spread captures increases in frictions of financial conditions affecting all firms simultaneously. By running (4) we are able to disentangle and test for those differences across the two groups. We present these results in columns (3) (4) and (5) of Table 4.

Starting with the classification of firms based on the S&P credit ratings in column (3), we see that ex-ante unconstrained firms significantly drop their investment in response to uncertainty shocks ($\beta_1 = -0.028$, significant at the 5%), particularly during years of high financial frictions ($\beta_2 = -0.022$, significant at the 5%), for a total significant effect of $\beta_1 + \beta_2 = -0.050$, and a *within-unconstrained-group* amplification effect at $(-0.050/-0.028) = 1.79$. In addition to the within-group amplification effects, the point estimates also allow us to compare the size of the effects across the two groups: the *cross-group total amplification effect* is $(\beta_1 + \beta_2 + \beta_4 + \beta_7)/(\beta_1 + \beta_2) = (-0.071/-0.050) = 1.42$.[25]

We see similar inferences using other common measures of firm-level financial constraints when classifying firms ex-ante. Using the SA index of Hadlock and Pierce (2010) in column (4), we find that unconstrained firms significantly respond to uncertainty shocks and more so in high financial friction years ($\beta_1 = -0.025$ and $\beta_2 = -0.026$, respectively and both significant at the 5%), for a total effect in high financial friction years of -0.051, and an even larger *within-unconstrained-group* amplification effect at $-0.051/-0.025 = 2.04$. The SA index also confirms that the total negative effects on investment are, indeed, larger for the

[25] Testing whether this *cross-group total amplification effect* $FUM = 1.42 > 1$ is significant is simply another way of rewritting our formal alternative hypothesis $H_a : \beta_4 + \beta_7 < 0$ presented at the bottom of column (2), which has a null p-value of 0.045, and thus we reject the null that ex-ante unconstrained firms see at least equal negative effects on investment relative to constrained firms

ex-ante constrained firms during high frictions with a *cross-group total amplification effect* $-0.078/-0.056 = 1.37$ (p-value 0.057). Using the Whited-Wu constraint measures in column (5) also gives comparable amplification as those implied by the S&P ratings and SA indexes.

Figure 2 shows the average impact of uncertainty in our sample of firms given our key results in column (3) of Table 4. In particular, it uses the time variation in both the credit spread and the mix of financially constrained firms using the S&P rating to generate the *marginal impact of uncertainty on investment* (weighted by employment size). We see that in normal times (e.g. around 2005) the mean impact of firm uncertainty on investment as a fraction of lagged capital stock is around -2.0 percentage points (which in standard deviation units, means that a two SD uncertainty shock reduces the rate of investment by about 1.2 percentage points). Strikingly, however, during the 2008-2009 crisis, because of both the rise in the credit spread and the drop in S&P rating for many firms, the mean impact of uncertainty approximately tripled to -6.0 points. Thus, on aggregate for our sample of firms, we see a quadrupling of the impact of uncertainty during the financial crisis, which highlights the interaction of financial conditions and rising uncertainty.

Columns (3) (4) and (5) indicate that the causal effects of uncertainty on investment differs between constrained and unconstrained firms *particularly* in years of heightened financial frictions (as identified by jumps in the Moody's credit spread). As seen in column (2), however, in a year of average credit frictions there is no difference in intensity between the two groups. Another way of confirming the underlying idea that uncertainty shocks and financial frictions combine to amplify the negative effects of uncertainty is by shifting the timing of the tightening of the aggregate credit conditions. We do so in columns (6) and (7) we run a placebo - instead of measuring the Moody's credit spread at year t and contemporaneously to the LHS investment outcome as in columns (1) (3) (4) (5), we shift the credit spread by $t-3$ years.

This is a placebo falsification test for the role of heightened credit conditions amplifying the effect of uncertainty. The idea is that if we shift the spike in the market-wide credit frictions of,

say, the 2008-2009 financial crisis to instead be measured in 2005-2006 placebo years, we should not find any amplification effect on the role of uncertainty. Indeed, column (6) shows that the negative effect of uncertainty on investment remains significant for years of average credit frictions ($\beta_1 = -0.028$, significant at the 5%) yet there is no amplification effect coming from heightened placebo credit friction years ($\beta_2 = 0.002$ insignificant), which is in sharp contrast to the amplifications effects seen in column (1). Similarly, column (7) presents the placebo equivalent of column (3) that uses the S&P firm credit rating constraints classification, and shows that both the *within-unconstrained* and *within-constrained amplifications* effects are no longer present. Moreover, the strong *cross-group total amplification effect* of 1.42 in column (3) is now $(\beta_1+\beta_2+\beta_4+\beta_7)/(\beta_1+\beta_2) = (-0.028/-0.031) = 0.90$, with a $p-value = 0.617$ that strongly fails to reject the null that ex-ante unconstrained firms see comparable effects from uncertainty relative to constrained firms. We see similar results if we shift the credit spread by additional lags (e.g., $t-5$) and/or use the other common financial constraints measures used in columns (4) and (5).

A concern could be whether Moody's credit spread is a good measure of aggregate financial frictions. In Table 5 we examine the amplification effects on investment using 4 different measures proposed in the literature to account for aggregate financial frictions. These proxies are the US financial distress measure by Romer and Romer (2017) in columns (1) and (2), a series that assesses "the health of the US financial system", the Chicago Fed National Financial Conditions Index (NFCI) in (3) and (4), a series that "has been historically associated with tighter-than-average financial conditions", the Chicago Fed Adjusted National Financial Conditions Index (ANFCI) in (5) and (6), which adjusts the NFCI index for the role of first moment economic conditions (in particular, it "isolates a financial-only element of conditions, which adjusts for the state of the business cycle and the level of inflation"), and the financial soundness index by Atkeson, Eisfeldt, and Weill (2017) in (7) and (8), an aggregate state variable based on the distribution of distance to insolvency of firms that accounts for "the financial soundness of all US firms". These four series are standardized to ease interpretation

of coefficients and make the point estimates directly comparable to those discussed above in Table 4 that use Moody's credit spread.

Starting with the Romer and Romer (R&R) financial distress measure in columns (1) of Table 5 by running model 3, we see a similar total effect of uncertainty on investment relative to using our baseline Moody's credit spread in column (1) in Table 4. The total negative effect of uncertainty on investment during heightened financial frictions amounts to a drop in investment of 6.0 percentage points using Moody's spread in column (1), while the financial distress measure by R&R implies a drop in investment of 6.3 percentage points. Using the Chicago Fed NFCI index in column (3) implies a similar drop of 6.2 points, while adjusting this index for the role of economic conditions of the business cycle and inflation in column (5) using the adjusted ANFCI index gives a larger effect of uncertainty at a drop of 8.4 percentage points, and using the financial soundness state variable in column (7) a drop of 7.2 percentage points. The amplification effect across the 4 different measures for financial frictions $(\beta_1 + \beta_2)/\beta_1$ when going from normal to high frictions is sizable and significant at 1% in all cases, ranging from 1.95 to 2.69.

Running model 4 in columns (2) (4) (6) (8) to disentangle and quantify the differences in the effects of uncertainty for firms with less and more binding constraints, we see that regardless of the proxy used for measuring financial frictions ex-ante financially constrained firms respond more intensively to uncertainty shocks than unconstrained firms.

In summary, Tables 4 and 5 and Figure 2 suggest that financial frictions amplify the negative effects of uncertainty shocks on real investment activity of firms. We also find evidence of an amplification effect through financial frictions for other real outcome variables, which we discuss in Appendix section A.11. The next section presents the model that discusses the mechanism for the amplification effect for uncertainty.

4 Model

The model features a continuum of heterogeneous firms facing uncertainty shocks and real adjustment costs as in Cooper and Haltiwanger (2006). Firms implement risk management policies by saving in cash as in Froot, Scharfstein, and Stein (1993). We do not explicitly model financial intermediation, instead we summarize the costs associated with external financing with a simple functional form that captures the basic idea that there is a wedge between internal and external funds and that external funds are more costly than internal funds. Furthermore, financial adjustment costs vary over time and across firms. Firms choose optimal levels of physical capital investment, labor, and cash holding each period to maximize the market value of equity.

To illustrate the intuition of the model mechanism we analyze the policy functions implied by two different model specifications: 1) the model with real adjustment costs only (real), and 2) the model with real and financial adjustment costs (real+financial).[26] Figures 3A and 3B plot the optimal investment policies associated with low and high uncertainty states of the real-only model (top left) and the benchmark model (top right), respectively. In both figures we fix the idiosyncratic productivity and cash holding at their median grid points and the financial shock at the low state. In the real-only fixed adjustment cost model, optimal investment displays the classic Ss band behavior. There is an investing region when the firm size (capital) is small, an inaction region when the firm size is in the intermediate range, and an disinvestment region when the firm is large. Moreover, the Ss band expands with higher uncertainty due to the real-option effects inducing greater caution in firms investment behavior. Turning to the real+financial model we again see that the Ss band associated with high uncertainty state is bigger than the low uncertainty state. However, optimal investment in the baseline model displays a second flat region, which arises when the firm is investing but only financed by internal funds. This happens because firms are facing binding financial constraints ($E_t = 0$), and are not prepared to pay the fixed costs of raising external equity.

[26] We use the same parameter values as in the model in Section (5).

Overall, this shows two results. First, real and financial constraints interact to expand the central region of inaction in Ss models. Second, uncertainty leads to a greater increase in the width of the Ss bands with both real and financial adjustment costs because it increases the value of real-options (the option to delay investing) and cash-options (the option to delay raising finance). This is the mechanism driving the amplification of financial frictions to the uncertainty shock. We now turn to the model details.

4.1 Technology

Firms use physical capital (K_t) and labor (L_t) to produce a homogeneous good (Y_t). To save on notation, we omit the firm index whenever possible. The production function is Cobb-Douglas, given by

$$Y_t = \widetilde{Z}_t K_t^{\alpha} L_t^{1-\alpha}, \tag{6}$$

in which $\widetilde{Z}_t$ is firms' productivity. The firm faces an isoelastic demand curve with elasticity (ε),

$$Q_t = BP_t^{-\varepsilon}, \tag{7}$$

where B is a demand shifter. These can be combined into a revenue function $R\left(Z_t, B, K_t, L_t\right) = \widetilde{Z}_t^{1-1/\varepsilon} B^{1/\varepsilon} K_t^{\alpha(1-1/\varepsilon)} \left(L_t\right)^{(1-\alpha)(1-1/\varepsilon)}$. For analytical tractability we define $a = \alpha\left(1-1/\varepsilon\right)$ and $b = \left(1-\alpha\right)\left(1-1/\varepsilon\right)$, and substitute $Z_t^{1-a-b} = \widetilde{Z}_t^{1-1/\varepsilon} B^{1/\varepsilon}$. With these redefinitions we have revenue redefined as

$$S\left(Z_t, K_t, L_t\right) = Z_t^{1-a-b} K_t^a L_t^b. \tag{8}$$

Wages are normalized to 1 denoted as $\bar{W}$. Given employment is flexible, we can obtain optimal labor.[27] Note that labor can be pre-optimized out even with financial frictions which will be discussed later.

Productivity is defined as a firm-specific productivity process, following an AR(1) process

$$z_{t+1} = \rho_z z_t + \sigma_t \varepsilon_{t+1}^z, \tag{9}$$

[27] Pre-optimized labor is given by $\left(\frac{b}{\bar{W}} Z_t^{1-a-b} K_t^a\right)^{\frac{1}{1-b}}$.

in which $z_{t+1} = \log(Z_{t+1})$, ε^z_{t+1} is an i.i.d. standard normal shock (drawn independently across firms), and ρ_z, and σ_t are the autocorrelation and conditional volatility of the productivity process.

The firm stochastic volatility process is assumed for simplicity to follow a two-point Markov chains

$$\sigma_t \in \{\sigma_L, \sigma_H\}, \text{where } \Pr(\sigma_{t+1} = \sigma_j | \sigma_t = \sigma_k) = \pi^{\sigma}_{k,j}. \tag{10}$$

Physical capital accumulation is given by

$$K_{t+1} = (1 - \delta)K_t + I_t, \tag{11}$$

where I_t represents investment and δ denotes the capital depreciation rate.

We assume that capital investment entails nonconvex adjustment costs, denoted as G_t, which are given by:

$$G_t = c_k S_t \mathbf{1}_{\{I_t \neq 0\}}, \tag{12}$$

where $c_k > 0$ is constant. The capital adjustment costs include planning and installation costs, learning to use the new equipment, or the fact that production is temporarily interrupted. The nonconvex costs $c_k S_t \mathbf{1}_{\{I_t \neq 0\}}$ capture the costs of adjusting capital that are independent of the size of the investment. They are scaled by firms' revenue so that firms do not outgrow adjustment costs in the model.

We also assume that there is a fixed production cost (F_t) which depends on lagged productivity, $F_t = f Z_{t-1}$ with $f > 0$ as a constant.[28] Firms need to pay this cost regardless of investment and hiring decisions every period, and is important for motivating firms to hold cash to cover costs of production. Hence firms' operating profit (Π_t) is revenue minus wages and fixed cost of production, given by

$$\Pi_t = S_t - \bar{W} L_t - F_t. \tag{13}$$

[28] We started by wanting to assume fixed cost are a function of lagged revenue S_{t-1}, i.e., $F_t = \tilde{f} S_{t-1}$. This is both to reflect the fact the overheads are likely related to prior size, and numerically to avoid large firms outgrowing fixed costs. However, this poses a numerical challage because it requires carrying an extra highly partitioned state variable S_{t-1}. Hence, we make the approximation that $F_t = f Z_{t-1}$ - that is fixed costs are a function of lagged productivity. The justification is that lagged sales are highly correlated with lagged productivity (correlation of 0.96 in the model since K_{t-1} and L_{t-1} are both highly corelated with Z_{t-1}), and lagged productivity is an existing state variable so this does not increase computational burden.

4.2 Cash holding

Firms save in cash (N_{t+1}) which represents the liquid asset that firms hold. Cash accumulation evolves according to the process

$$N_{t+1} = (1 + r_n) N_t + H_t, \tag{14}$$

where H_t is the investment in cash and $r_n > 0$ is the return on holding cash. Following Cooley and Quadrini (2001) and Hennessy, Levy, and Whited (2007), we assume that return on cash is strictly less than the risk free rate r_f (i.e., $r_n < r_f$). This assumption is consistent with Graham (2000) who documents that the tax rates on cash retentions generally exceed tax rates on interest income for bondholders, making cash holding tax-disadvantaged. Lastly, cash is freely adjusted.

4.3 External financing costs

The final part of the model concerns the external financing costs. We do not model financial intermediation costs endogenously associated with asymmetric information as in Myers and Majluf (1984) or agency frictions in Jensen and Meckling (1976). Instead we choose to summarize the costs of external financing in a reduced form way as in Gomes (2001), Hennessy and Whited (2005) and Bolton, Chen, and Wang (2011). Specifically, when the sum of investment in capital, investment adjustment cost and investment in cash exceeds the operating profit, firms can take external sources of funds as a last resource. The financing costs include both direct costs (for example, flotation costs - underwriting, legal and registration fees), and indirect (unobserved) costs due to asymmetric information and managerial incentive problems, among others.[29]

Because external financing costs will be paid only if payouts are negative, we define the firm's payout before financing cost (E_t) as operating profit minus investment in capital and

[29]These costs are estimated to be substantial. For example, Altinkilic and Hansen (2000) estimate the underwriting fee ranging from 4.37% to 6.32% of the capital raised in their sample. In addition, a few empirical papers also seek to establish the importance of the indirect costs of equity issuance. Asquith and Mullins (1986) find that the announcement of equity offerings reduces stock prices on average by −3% and this price reduction as a fraction of the new equity issue is on average −31%.

cash accumulation, less investment adjustment costs

$$E_t = \Pi_t - I_t - H_t - G_t. \tag{15}$$

Furthermore, external financing costs vary over time and across firms, consistent with Erel, Julio, Kim, and Weisbach (2012) who show that firms' access to external finance markets also changes with macroeconomic conditions.[30] The micro-foundations of time-varying financing conditions include endogenous time-varying adverse selection problems in Eisfeldt (2004), Kurlat (2013), and Bigio (2015) who show that uncertainty increases the adverse selection cost from external financing, agency frictions varying over time as in Bernanke and Gertler (1989) and Carlstrom and Fuerst (1997), and time-varying liquidity as in Pastor and Stambaugh (2003). Furthermore, empirically, Choe, Masulis, and Nanda (1993) find that the adverse selection costs measured as negative price reaction to seasoned equity offering announcement is higher in contractions and lower in expansions, suggesting changes in information symmetries between firms and investors are likely to vary over time.[31]

As such, we use η_t to capture the time-varying financing conditions that also vary across firms; it is assumed for simplicity to follow a two-point Markov chain

$$\eta_t \in \{\eta_L, \eta_H\}, \text{where } \Pr\left(\eta_{t+1} = \eta_j | \eta_t = \eta_k\right) = \pi^{\eta}_{k,j}. \tag{16}$$

We do not explicitly model the sources of the external financing costs. Rather, we attempt to capture the effect of the costs in a reduced-form fashion. In addition, we make general assumptions about the financing costs which include all kinds of costly external financing activities, namely, costs associated with all marginal sources of financing for firms when payouts are negative.[32] Specifically, the external financing costs Ψ_t are assumed to be

[30] Kahle and Stulz (2013) find that net equity issuance falls more substantially than debt issuance during the recent financial crisis suggesting that shocks to the corporate credit supply are not likely to be the cause for the reduction in firms' capital expenditures in 2007-2008.

[31] In addition, Lee and Masulis (2009) show that seasoned equity issuance costs are higher for firms with poor accounting information quality.

[32] In the robustness section we extend the model by explicitly modelling two common marginal external financing channels separately, i.e., costly external equity and collaterilzed debt. We show that our result remains robust.

proportional to the proceeds raised[33]:

$$\Psi_t = \phi(\eta_t, \sigma_t) |E_t| \mathbf{1}_{\{E_t<0\}}. \tag{17}$$

Firms do not incur costs when paying dividends or repurchasing shares. So $\phi(\eta_t, \sigma_t)$ captures the marginal cost of external financing which affects both optimal investment and cash holding policies, similar to Eisfeldt and Muir (2016) who model a time-varying financing condition by an AR(1) process.

Finally, note that the marginal external financing cost depends on both time-varying financing condition η_t and time-varying uncertainty σ_t, which captures the fact that periods of high external financing costs are associated with heightened uncertainty. This assumption is consistent with the empirical evidence that uncertainty (proxied by the VIX) and external financing costs (proxied for by the total external financing costs constructed by Eisfeldt and Muir (2016), the SLOOS Index of lending standards and the Baa-Aaa credit spread) are highly positively correlated.[34] In addition, Caldara, Fuentes-Albero, Gilchrist, and Zakrajsek (2016) document that change in VIX and change in CDS spread are positively correlated. As such, we assume $\phi(\eta_t, \sigma_t) = \eta_t + \lambda$ with $\lambda > 0$ when $\sigma_t = \sigma_H$, and $\phi(\eta_t, \sigma_t) = \eta_t$ when $\sigma_t = \sigma_L$, to capture the positive correlation between financing cost and uncertainty shock in the data.

4.4 Firm's problem

Firms solve the maximization problem by choosing capital investment, labor, and cash holding optimally:

$$V_t = \max_{I_t, L_t, K_{t+1}, N_{t+1}} [E_t - \Psi_t + \beta \mathbb{E}_t V_{t+1}], \tag{18}$$

subject to firms' capital accumulation equation (Eq. 11) and cash accumulation equation (Eq. 14), where $E_t - \Psi_t$ captures the net payout distributed to shareholders.

[33]We have also solved the model with fixed financing costs which does not depend on the external funds raised in the NBER working paper No. 24571. We now use proportion financing costs because it is more likely to be the primary form of costs that firms face when raising external funds. However, the amplification effect of financial frictions remains robust. The intuition is that both fixed and proportional external financing costs enlarge the Ss band of investment relative to the model with only fixed investment cost, thus amplify the negative impact of uncertainty shock on investment.

[34]We provide detailed analysis for this result in Section 5.4.

5 Main results

This section presents the model solution and the main results[35]. We first calibrate and estimate the model parameters, then we simulate the model and study the quantitative implications of the model for the relationship between uncertainty shocks, financial shocks, and firms' real activity and financial flows. The full set of parameters is the vector θ that characterizes the firm's revenue function, stochastic processes, real and financial adjustment costs, return-on-cash and discount rate. The econometric problem consists of estimating this parameter vector θ. Since the model has no analytical closed form solution, this vector cannot be estimated using standard regression techniques. Instead estimation of the parameters is achieved by simulated method of moments (SMM), which minimizes a distance criterion between key moments from actual data (a panel of publicly traded firms from Compustat) and simulated data. Because SMM is computationally intensive, only 4 parameters are estimated; the remaining 14 are predefined.

5.1 Simulated Method of Moments

SMM proceeds as follows: a set of actual data moments Ψ^A is selected for the model to match.[36] For an arbitrary value of θ the dynamic program is solved and the policy functions are generated. These policy functions are used to create a simulated data panel of size $(N, T + 800)$, where N is close to the number of firms in the actual data, and T is close to the time dimension of the actual data. The first 800 quarters are discarded so as to start from the ergodic distribution. The simulated moments $\Psi^S(\theta)$ are then calculated on the remaining simulated data panel, along with an associated criterion function $\Gamma(\theta)$, where $\Gamma(\theta) = \left[\Psi^A - \Psi^S(\theta)\right]' W \left[\Psi^A - \Psi^A(\theta)\right]$, which is a weighted distance between the simulated moments $\Psi^S(\theta)$ and the actual moments Ψ^A.

The parameter estimate θ is then derived by searching over the parameter space to find

[35] See https://people.stanford.edu/nbloom/ for the full Matlab code to replicate all results.

[36] See McFadden (1989) and Pakes and Pollard (1989) for the statistical properties of the SMM estimator.

the parameter vector which minimizes the criterion function:

$$\hat{\theta} = \arg\min_{\theta \in \Theta} \left[\Psi^A - \Psi^S(\theta)\right]' W \left[\Psi^A - \Psi^S(\theta)\right]. \tag{19}$$

Given the potential for discontinuities in the model and the discretization of the state space, we use an annealing algorithm for the parameter search (see Appendix B.2). Different initial values of θ are selected to ensure the solution converges to the global minimum. We also run robustness tests in Section C.1 with different initial distributions.

5.2 Predetermined parameters

In principle every parameter could be estimated, but in practice the size of the estimated parameter space is limited by computational constraints. We therefore focus on the parameters about which there are probably the weakest priors—the real adjustment cost parameter, the low/high financing costs, and the impact of uncertainty for financing costs parameter, $\Theta = (c_k, \eta_L, \eta_H, \lambda)$. The other parameters are based on values in the data and the prior literature, and are reported in Table 6. Below we briefly discuss how we calibrate the parameters of the baseline model. Appendix Section C provides a detailed discussion of the calibration for some of the key parameters.

We set the share of capital in the production function at 1/3, and the elasticity of demand ε to 4 which implies a markup of 33%, toward the upper end of estimates for price–cost markups in Hall (1988). The capital depreciation rate δ is set to be 3% per quarter. The discount factor β is set so that the real firms' discount rate $r_f = 5\%$ per annum, which implies $\beta = 0.988$ quarterly. Return-on-cash saving r_n is assumed to be less than the risk-free rate due to the tax disadvantage of carrying cash for firms or agency frictions associated with cash holding. Given that there is no readily available estimate for r_n, we set return-on-cash $r_n = 50\% r_f$ and also check robustness of $r_n = 75\% r_f$.

The fixed operating cost f is set to 20% such that the fixed cost to the average revenue ratio is 15%, consistent with the average SGA-to-sales ratio of 15% in Compustat data. Wage rate $\bar{W}$ is normalized to 1. We set the persistence of firms' micro productivity as $\rho_z = 0.95$

following Khan and Thomas (2008). Following Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018), we set the baseline firm volatility as $\sigma_L = 0.051$, the high uncertainty state $\sigma_H = 4 * \sigma_L$, and the transition probabilities of $\pi^{\sigma}_{L,H} = 0.026$ and $\pi^{\sigma}_{H,H} = 0.943$. Because there is no readily available estimate for the transition probabilities of financial shock in the data, and to keep this symmetric with uncertainty to facilitate interpretation of the results, we set them the same as those of the uncertainty shock.[37]

5.3 Estimation

Under the null, a full-rank set of moments $\left(\Psi^A\right)$ will consistently estimate the parameter of the real and financial adjustment costs (Θ). The choice of moments is also important for the efficiency of the estimator. This suggests that moments which are "informative" about the underlying structural parameters should be included. Given that we are exploring the impact of uncertainty shocks for both real and financial outcomes, we choose the coefficients of the multivariate IV regressions (Column 6 of Tables 1, 2 and 3) of investment rate, employment growth, cash growth and dividend growth as the moments to match.

5.4 Baseline estimation results

We compare panel regression data from the simulation of different model specifications to the real data. Specifically, we regress the rates of investment, employment growth, cash growth and dividend payout growth (defined as positive payout growth) on the growth of volatility ($\Delta\sigma_t$) at quarterly frequency, alongside a full set of firm and year fixed-effects. Using the true volatility growth in the model allows us to mimic the IV regressions for the real data regressions.

The top panel in Table 7 reports the estimated parameters. The Column 2 labelled Baseline presents the results from estimating the preferred specification with both real and external financial adjustment costs. The estimated real adjustment costs for capital imply

[37] We also estimated the model with different transition probabilities for financial shocks, e.g., $\pi^{\eta}_{L,H} = 5\%$ and $\pi^{\eta}_{H,H} = 50\%$. The quantitative result is similar to the baseline calibration as shown in Figure 6.

fixed investment costs of 3.6% of sales (conditional on investing or disinvesting). The estimated financial adjustment costs imply low/high state financing costs of 0.1%/45.6% of the proceeds raised from external financial markets (conditional on issuing). The standard errors suggest all of these point estimates are statistically significant. Because external financing costs include both direct costs, e.g., flotation costs and indirect costs due to asymmetric information, there are no empirical estimates for the total cost that we can compare with. The model implied average financing costs are 7% of the funds raised (not tabulated), within the range of the estimates in Altinkilic and Hansen (2000) and Hennessy and Whited (2005).

Column 1 of the middle panel of Table 7 presents the results from the real data (replicated from section 3) as a benchmark. As we saw investment, employment and equity payouts significantly drop after an increase in uncertainty while cash holdings rises.[38] Column 2 presents the baseline model simulation results, and finds the baseline model fits the data well with drops in investment, employment (due to "real options" effects of uncertainty), and drops in equity payouts and rising cash holdings (due to "cash options" effects of uncertainty).[39]

For interpretation, in Table 7 we also display results for three illustrative restricted models. First, a model with real adjustment cost only (Real-only), assuming financial markets are free of frictions, as is typical in the investment literature. In Column 3 we see that estimated real adjustment costs imply 23.3% of sales as fixed investment costs, much larger than the baseline model. This implies that the typical model (real-only) used in the investment literature over-estimates the fixed investment costs because the model ignores financial costs. The Real-only model's fit is also worse than the baseline, because it implies zero cash growth (there is no cash holding in this model). In addition, it also implies a positive coefficient on dividend growth, which is counterfactual. Second, a model with external financing cost only (Financial-only), assuming real adjustment cost is zero. In Column 4, we see the Financial-only model can generate positive impact on cash and negative impact on dividends (due to cash options

[38] All results in this table are significant at the 1% (with firm-clustered standard errors), hence we do not report t-statistics for simplicity.

[39] The employment growth coefficient is lower than the data because the model does not have labor adjustment cost.

effects), but the fit of Financial-only model on real outcomes is particularly poor. In fact, it implies positive coefficients on investment and employment growth, opposite to the data. Lastly, a model without any adjustment costs, leading to substantially worse fit of the data, reported in Column 5. Since the model has no adjustment costs, it results in very small positive Oi-Hartman-Abel impacts on investment and employment, no cash impacts, and large dividend impacts due to more fluctuations in equity payouts.

5.5 Inspecting the mechanism

5.5.1 Impulse responses

We simulate the impulse responses of the baseline model and other model specifications with real frictions only and financial frictions only. We run our model with $30,000$ firms for 800 periods and then kick uncertainty and/or financing costs up to its high level in period 801 and then let the model to continue to run as before. Hence, we are simulating the response to a one period impulse and its gradual decay. Overall, we show that real frictions alone cannot generate persistent impact of uncertainty shocks, whereas financial frictions alone leads to persistent medium term response but counterfactual positive short-term response in output; combining both types of frictions is important to generate large drops in quantities but also persistent responses and slow recoveries.

Uncertainty shocks Figure 4 plots the impulse responses of the real and financial variables of the benchmark model to a pure uncertainty shock. Starting with the classic "real adjustment cost" only model (black line, x symbols) we see a peak drop in output of 1.7% and an overshoot above the trend. This is driven by drops and recoveries in capital, labor and TFP. Capital and labor drop and recover due to real-option effects leading firms to pause investing (and thus hiring by the complementarity of labor and capital), while depreciation continues to erode capital stocks. TFP falls and recovers due to the increased misallocation of capital and labor after uncertainty shocks - higher uncertainty leads to more rapid reshuffling of productivity across firms, which with reduced investment and hiring leads to more input

misallocation. Dividend payout rises because firms with excess capital disinvest more with high uncertainty and hence payout more. It is worth noting that the Real-only model cannot generate persistent drop in output, capital or labor. Real adjustment costs lead to a sharp drop due to the Ss band expansion which freezes investment after the shock, but with a rapid bounce-back as the Ss bands contract and firms realize pent-up demand for investment. In fact, capital overshoots after the uncertainty shock.

Turning to the baseline model (red line, triangle symbols) with "real and financial adjustment costs" we see a much larger peak drop in output of 3.6%, alongside larger drops in capital and labor. Hence, we again see that adding financial costs to the classic model roughly doubles the impact of uncertainty shocks. Furthermore, the interaction of financial costs with uncertainty generates a desire by the firms to increase cash holdings when uncertainty is high, leading to more persistent drops in output, capital and labor. The duration of impact is roughly doubled compared to the baseline - output and labor fall for 3 periods rather than 2, while capital falls for 3 periods rather than 1.

Finally, the model with only "financial adjustment costs" (blue line, circles) leads to a similar 3.7% peak drop in output. This is driven by a similar drop in capital as financial adjustment costs reduces availability of external funds and leads firms to hoard cash after an uncertainty shock, while labor also drops (since this is complementary with capital), as does TFP due to less investment and hiring raising misallocation. However, with financial costs alone, the uncertainty shock leads to an increase in output, capital and labor upon impact since firms invest in capital when there is no real adjustment costs. In the medium term investment drops back down as firms shift towards building up cash reserves.

Combined uncertainty and financial shocks As Stock and Watson (2012) suggest combined financial and real shocks are a common occurrence, and indeed these both occurred in 2007-2009, so we examine the impact of this in Figure 5.[40] This plots the impact in the benchmark model of an uncertainty shock (red line, triangle), a financial shock (green line,

[40]We see spikes in capital, labor and output here and in Figure 4 as well. This is the echo effect caused by fixed costs analyzed in Gourio and Kashyap (2007).

circle) and both shocks simultaneously (purple line, x symbols).

The main result from Figure 5 is that both uncertainty and financial shocks individually lead to drops in output, capital, labor and TFP of broadly similar sizes. But collectively their impact is significantly larger and more persistent - for example, the drop in output from an uncertainty or financial shock alone is 3.6% and 3.7% respectively, while jointly they lead to an output fall of 5.3%. This highlights that combined financial and uncertainty shocks lead to substantially larger drops in output, investment and hiring, alongside increases in cash holdings and reductions in equity payouts. As we saw in Figure 1 this occurred in 2007-2009, suggesting modeling this as a joint finance-uncertainty shock will come closer to explaining the magnitude of this recession.

Robustness We consider changes in parameter values, general equilibrium and an extended model with collateralized debt (details in section C.1). These models implied impulse responses are plotted in Figure 6. The broad summary is that while the quantitative results vary somewhat across different models, the qualitative results are robust - uncertainty shocks lead to drops and rebounds in output, capital and labor (alongside rises in cash and drops in equity payouts), and adding in financial adjustment costs make the impact larger and more persistent.

5.5.2 Magnitude of adjustment costs

Notably, despite of the large amplification effect and the persistent responses generated by adding financial frictions, the magnitude of financial costs is small. In particular, in the baseline model the aggregate financial adjustment cost is only 0.05% of the aggregate revenue, much smaller than the aggregate real adjustment costs, which is 0.3% of the aggregate revenue, as reported in the bottom panel of Table 7. Moreover, the total adjustment costs in the baseline model is 0.35% of the aggregate revenue, roughly *half* of the total adjustment costs in the Real-only model. This implies that the strong amplification of financial frictions does not rely on larger total adjustment costs. The intuition is that Ss bands are extremely sensitive

to adjustment costs around zero, so even very small adjustment costs can have large impacts on firm behavior. That's why despite financial frictions that are small in magnitude, they significantly amplify the impact of uncertainty shocks.

5.6 The interactions between uncertainty shocks and financial frictions

This section examines the interactions between financial frictions and uncertainty shocks. To do this in a panel setting we first solve the financially constrained model with different values of financing costs, and then compare firms' response to uncertainty to the same model with no financial adjustment costs. This comparison is undertaken in following regression, which combines the constrained and unconstrained firms in one panel

$$\frac{I_{i,t}}{K_{i,t-1}} = a + b \cdot \Delta\sigma_{i,t} + c \cdot (\Delta\sigma_{i,t} \cdot D_i^{Fin.Const}) + D_i^{Fin.Const} + \delta_i + \phi_t + \varepsilon_{i,t}, \qquad (20)$$

where $\Delta\sigma_{i,t}$ are firm uncertainty shocks, $D_i^{Fin.Const}$ is a dummy variable with value 1 for constrained firms (facing real and financial adjustment costs) and 0 for unconstrained firms (facing only real costs). We also include firm δ_i and time ϕ_t fixed effects. A negative value on the coefficient b captures the direct impact of uncertainty, and coefficient c captures the amplification effect of financial frictions for uncertainty.

In Table 8 we report the coefficients of b and c for the data (replicating column (2) from Table 4) and three levels of financial costs in the model (columns (2) to (4)). We see in column (2) that in our baseline model financially constrained firms have an amplification effect of 1.37, meaning they reduce investment by about one third more in response to uncertainty shocks that unconstrained firms. In column (3) we reduce financial constraints to 0.5 times the baseline and find this amplification is only 1.18, while in column (4) we increase financial constraints to 1.5 times the baseline and find an amplification effect of 1.46. Hence, higher steady-state levels of financial constraints in our simulation model lead to more negative impacts of uncertainty shocks on investment.

To look at this more generally in Figure 7 we plot the coefficients c associated with different

values of financing costs from 0.1 to 1.9. We see a monotonically decreasing relationship between c and the financing costs. That is, the more financially constrained a firm is the more it cuts investment when uncertainty is high.

6 Conclusion

This paper studies the impact of uncertainty shocks on firms' real and financial activity. We first take endogeneity concerns in measuring the effects of uncertainty seriously by employing a novel instrumentation strategy that exploits cross-sectional non-directional exposures to different aggregate sources of uncertainty. Using 2SLS estimations we document a large and causal effect of uncertainty shocks on both real and financial variables of firms. Uncertainty shocks reduce firms' investment (tangible and intangible), employment, sales and cost of good sold, while increasing cash holdings and reducing debt and corporate dividend payout.

Second, we document a larger negative impact of uncertainty on investment in years of heightened financial frictions, particularly for financially constrained firms. The combined effect of this is to increase the impact of uncertainty shocks up to three fold during periods of increased financial frictions (e.g. 2008-09) compared to periods of normal financial conditions (e.g. 2005-06). This explains how in recessions - when financial conditions typically deteriorate - uncertainty shocks can be so damaging for growth.

We then build a dynamic model which includes two key components: first, real and financial frictions, and second, uncertainty and financial shocks. This delivers three key insights. First, *amplification* - combining real and financial frictions roughly doubles the impact of uncertainty shocks on output. Furthermore, combining an uncertainty shock with a financial shock in this model increases the impact by about another two thirds, since these shocks have an almost additive effect. Since uncertainty and financial shocks are highly collinear (e.g. Stock and Watson 2012) this is important for modelling their impacts. Second, *persistence* - adding financial frictions roughly doubles the duration of drops after an uncertainty shock. This is because financial frictions lead firms to become more financially conservative after

an uncertainty shock, reducing investment rates during the rebound. Finally, *propagation* - financial frictions spread the impact of uncertainty shocks to financial outcomes as well as real outcomes. In this model uncertainty shocks not only reduce investment and hiring, but also raise firms cash holding, while cutting equity payouts. Collectively, these predictions of a large, persistent and widespread impact of uncertainty shocks on real and financial variables matches the evidence from the recent financial crisis.

Taken together we believe that rather than trying to evaluate whether uncertainty shocks *or* financial constraints are responsible for the drop in investment, hiring and output growth during events like the 2008-2009 crisis, we should recognize and estimate their interactive amplification effects.

References

Abel, A., and J. Eberly (1996): "Optimal Investment With Costly Reversibility," *Review of Economic Studies*, 63, 581–593.

Alessandri, P., and H. Mumtaz (2018): "Financial regimes and uncertainty shocks," *Journal of Monetary Economics*.

Almeida, H., M. Campello, I. Cunha, and M. S. Weisbach (2014): "Corporate Liquidity Management: A Conceptual Framework and Survey," *Annual Review of Financial Economics*, 6, 135–162.

Almeida, H., M. Campello, and M. S. Weisbach (2005): "The Cash Flow Sensitivity of Cash," *Journal of Finance*, 59(4), 1777–1804.

Altinkilic, O., and R. S. Hansen (2000): "Are There Economies of Scale in Underwriting Fees? Evidence of Rising External Financing Costs," *Review of Financial Studies*, 13, 191–218.

Arellano, C., Y. Bai, and P. J. Kehoe (2019): "Financial Frictions and Fluctuations in Volatility," *Journal of Political Economy*, 127(5), 2049–2103.

Asquith, P., and D. Mullins (1986): "Equity issues and offering dilution," *Journal of Financial Economics*, 15, 61–89.

Atkeson, A. G., A. L. Eisfeldt, and P.-O. Weill (2017): "Measuring the financial soundness of U.S. firms, 19262012," *Research in Economics*, 71(3), 613–635.

Bachmann, R., and C. Bayer (2013): "Wait-and-See Business Cycles?," *Journal of Monetary Economics*, 60(6), 704–719.

Bachmann, R., and G. Moscarini (2012): "Business Cycles and Endogenous Uncertainty," *Working Paper, University of Notre Dame and Yale University*.

Baker, S., N. Bloom, and S. Davis (2016): "Measuring Economic Policy Uncertainty," *Forthcoming Quarterly Journal of Economics*.

Bansal, R., and A. Yaron (2004): "Risks for the long run: A potential resolution of asset pricing puzzles.," *Journal of Finance*, 59, 1481–1509.

Barro, R. (2006): "Rare disasters and asset markets in the twentieth century," *Quarterly Journal of Economics*, 121(3), 823–866.

Basu, S., and B. Bundick (2017): "Uncertainty Shocks in a Model of Effective Demand," *NBER Working Paper No. 18420*.

Bates, T. W., K. M. Kahle, and R. M. Stulz (2009): "Why Do U.S. Firms Hold So Much More Cash than They Used To?," *Journal of Finance*, 64(5), 1985–2021.

Baumol, W. (1970): "Earnings retention, new capital and the growth of the firm," *Review of Economics and Statistics*, 52, 345–355.

Berger, D., I. Dew-Becker, and S. Giglio (2016): "Contractionary volatility or volatile contractions?," *Working paper, Northwestern University*.

Bernanke, B., and M. Gertler (1989): "Agency costs, net worth, and business fluctuations," *American Economic Review*, 79(1), 14–31.

Bernanke, B. S. (1983): "Irreversibility, Uncertainty, and Cyclical Investment," *Quarterly Journal of Economics*, 98(1), 85–106.

Bernanke, B. S., M. Gertler, and S. Gilchrist (1999): "The financial accelerator in a quantitative business cycle framework," *Handbook of Macroeconomics*, 1, 1341–1393.

Bertola, G., and R. J. Caballero (1990): "Kinked Adjustment Costs and Aggregate

Dynamics," *NBER Macroeconomics Annual*, 5, 237–296.

Bigio, S. (2015): "Endogenous liquidity and the business cycle," *American Economic Review*, 105(6), 1883–1927.

Blanchard, O. J. (2009): "The Crisis: Basic Mechanisms and Appropriate Policies," *Working Paper*.

Bloom, N. (2009): "The Impact of Uncertainty Shocks," *Econometrica*, 77, 623–685.

Bloom, N., S. Bond, and J. V. Reenen (2007): "Uncertainty and investment dynamics," *Review of Economic Studies*, 74(2), 391–415.

Bloom, N., M. Floetotto, N. Jaimovich, I. Saporta-Eksten, and S. Terry (2018): "Really uncertain business cycles," *Econometrica*, 86(3), 1031–1065.

Bolton, P., H. Chen, and N. Wang (2011): "A unified theory of Tobin's q, corporate investment, financing, and risk management," *Journal of Finance*, 66, 1545–1578.

Bolton, P., H. Chen, and N. Wang (2013): "Market timing, investment and risk management," *Journal of Financial Economics*, 109, 40–62.

Bolton, P., N. Wang, and J. Yang (Forthcoming): "Liquidity and Risk Management: Coordinating Investment and Compensation Policies," *Journal of Finance*.

Caballero, R., E. Engel, and J. Haltiwanger (1995): "Plant-level adjustment and aggregate investment dynamics," *Brookings Papers on Economic Activity*, 2, 1–54.

Caggiano, G., E. Castelnuovo, and J. M. Figueres (2017): "Economic policy uncertainty and unemployment in the United States: A nonlinear approach," *Economics Letters*, 151, 31–34.

Caldara, D., C. Fuentes-Albero, S. Gilchrist, and E. Zakrajsek (2016): "The macroeconomic impact of financial and uncertainty shocks," *European Economic Review*, 88, 185–207.

Carhart, M. (1997): "On Persistence in Mutual Fund Performance," *Journal of Finance*, 52,1, 57–82.

Carlstrom, C. T., and T. S. Fuerst (1997): "Agency costs, net worth, and business fluctuations: A computable general equilibrium analysis," *American Economic Review*, 87(5), 893–910.

Chen, G. (2016): "Corporate Savings, Financing and Investment with Aggregate Uncertainty Shocks," *Working Paper, Nanyang Technological University*.

Chen, H., H. Wang, and H. Zhou (2014): "Stock Return Volatility and Capital Structure Decisions," *PBCSF-NIFR, Tsinghua University*, 13,04.

Chen, P., L. Karabarbounis, and B. Neiman (2017): "The global rise of corporate saving," *Journal of Monetary Economics*, 89, 1–19.

Choe, H., R. Masulis, and V. Nanda (1993): "Common Stock Offerings across the Business Cycle: Theory and Evidence," *Journal of Empirical Finance*, 1, 3–31.

Christiano, L. J., R. Motto, and M. Rostagno (2014): "Risk Shocks," *American Economic Review*, 104, 27–65.

Cooley, T. F., and V. Quadrini (2001): "Financial markets and firm dynamics," *American Economic Review*, 91, 1286–1310.

Cooper, R. W., and J. C. Haltiwanger (2006): "On the Nature of Capital Adjustment Costs," *Review of Economic Studies*, 73(3), 611–633.

Davis, S. J., and J. Haltiwanger (1992): "Gross Job Creation, Gross Job Destruction, and Employment Reallocation," *The Quarterly Journal of Economics, MIT Press*, 107,3,

819–863.

DeAngelo, H., L. DeAngelo, and T. M. Whited (2011): "Capital structure dynamics and transitory debt," *Journal of Financial Economics*, 99, 235–261.

Dixit, A. (1989): "Entry and Exit Decisions under Uncertainty," *Journal of Political Economy*, 97(3), 620–638.

——— (1993): "Choosing among alternative discrete investment projects under uncertainty," *Economics Letters*, 41(3), 265–268.

Dixit, A. K., and R. S. Pindyck (1994): *Investment under Uncertainty*. Princeton: Princeton University Press, Princeton, N.J.

Duchin, R., O. Ozbas, and B. Sensoy (2010): "Costly external finance, corporate investment and the subprime mortgage credit crisis," *Journal of Financial Economics*, 97, 418–435.

Eisfeldt, A. (2004): "Endogenous liquidity in asset markets," *Journal of Finance*, 59(1), 1–30.

Eisfeldt, A., and T. Muir (2016): "Aggregate External Financing and Savings Waves," *Journal of Monetary Economics*, 84, 116–133.

Eisfeldt, A., and D. Papanikolaou (2013): "Organization Capital and the Cross-Section of Expected Returns," *Journal of Finance*, 68(4), 1365–1406.

Erel, I., B. Julio, W. Kim, and M. Weisbach (2012): "Macroeconomic Conditions and Capital Raising," *Review of Financial Studies*, 25, 341–376.

Falgelbaum, P., E. Schaal, and M. Taschereau-Dumouchel (2016): "Uncertainty Traps," *Forthcoming, Quarterly Journal of Economics*.

Fernandez-Villaverde, J., P. Guerron-Quintana, K. Kuester, and J. Rubio-Ramirez (2015): "Fiscal Volatility Shocks and Economic Activity," *American Economic Review*, 105(11), 33523384.

Fernandez-Villaverde, J., P. G. Quintana, J. F. Rubio-Ramirez, and M. Uribe (2011): "Risk Matters: The Real Effects of Volatility Shocks," *American Economic Review*, 101,6, 2530–61.

Froot, K., D. Scharfstein, and J. Stein (1993): "Risk Management: Coordinating Corporate Investment and Financing Policies," *Journal of Finance*, 48(5), 1629–1658.

Gilchrist, S., J. Sim, and E. Zakrajsek (2014): "Uncertainty, Financial Frictions and Investment Dynamics," *Boston University mimeo*.

Gilchrist, S., and E. Zakrajsek (2012): "Credit spreads and business cycle fluctuations," *American Economic Review*, 102(4), 1692–1720.

Giroud, X., and H. M. Mueller (2017): "Firm Leverage, Consumer Demand, and Employment Losses During the Great Recession," *Quarterly Journal of Economics*, 132(1), 271–316.

Gomes, J. (2001): "Financing investment," *American Economic Review*, 65(2), 467–494.

Gomes, J. F., and L. Schmid (2010): "Levered Returns," *Journal of Finance*, 65(2), 467–494.

Gourio, F. (2012): "Disaster Risk and Business Cycles," *American Economic Review*, 102(6), 2734–2766.

Gourio, F., and A. K. Kashyap (2007): "Investment spikes: New facts and a general equilibrium exploration," *Journal of Monetary Economics*, 54(1), 1–22.

Graham, J. (2000): "How big are the tax benefits of debt?," *Journal of Finance*, 55(5),

1901–1941.

Guiso, L., and G. Parigi (1999): "Investment and Demand Uncertainty," *Quarterly Journal of Economics*, 114, 185–227.

Hadlock, C. J., and J. R. Pierce (2010): "New Evidence on Measuring Financial Constraints: Moving Beyond the KZ Index," *The Review of Financial Studies*, 23(5), 1909–1940.

Hall, R. E. (1988): "The Relation between Price and Marginal Cost in U.S. Industry," *Journal of Political Economy*, 96(5), 921–947.

Handley, K., and N. Limao (2012): "Trade and Investment under Policy Uncertainty: Theory and Firm Evidence," *NBER Working Paper 17790*.

Hennessy, C. A., A. Levy, and T. M. Whited (2007): "Testing Q theory with financing frictions," *Journal of Financial Economics*, 83(3), 691–717.

Hennessy, C. A., and T. M. Whited (2005): "Debt Dynamics," *Journal of Finance*, 60, 1129–1165.

——— (2007): "How costly is external financing? Evidence from a structural estimation," *Journal of Finance*, 62, 1705–1745.

Holmstrom, B., and J. Tirole (1998): "Private and public supply of liquidity," *Journal of Political Economy*, 106, 1–40.

Ilut, C., and M. Schneider (2014): "Ambiguous Business Cycles," *American Economic Review*, 104(8), 2368–99.

Jeffrey M Wooldridge (2015): *Introductory econometrics: A modern approach*. Cengage Learning.

Jensen, M. C., and W. H. Meckling (1976): "Theory of the Firm: Managerial Behavior, Agency Costs and Ownership Structure," *Journal of Financial Economics*, 3(4), 305–360.

Jeremy J. Siegel (1998): *Stocks for the Long Run : The Definitive Guide to Financial Market Returns and Long-Term Investment Strategies*. McGraw-Hill, New York.

Jermann, U., and V. Quadrini (2012): "Macroeconomic Effects of Financial Shocks," *American Economic Review*, 102(1), 238–71.

John Maynard Keynes (1936): *The general theory of employment, interest and money*. New York, Harcourt, Brace, New York.

Kahle, K., and R. Stulz (2013): "Access to Capital, Investment, and the Financial Crisis," *Journal of Financial Economics*, 110(2), 280–299.

Khan, A., and J. Thomas (2008): "Idiosyncratic Shocks and the Role of Nonconvexities in Plant and Aggregate Investment Dynamics," *Econometrica*, 76,2, 395–436.

King, R., and S. Rebelo (1999): *Handbook of Macroeconomics*. North-Holland, Amsterdam, Netherlands, Resuscitating real business cycles.

Krusell, P., and A. A. Smith (1998): "Income and Wealth Heterogeneity in the Macroeconomy," *Journal of Political Economy*, 106(5), 867–896.

Kurlat, P. (2013): "Lemons markets and the transmission of aggregate shocks," *American Economic Review*, 103(4), 1463–1489.

Leahy, J. V., and T. Whited (1996): "The Effect of Uncertainty on Investment: Some Stylized Facts," *Journal of Money, Creditand Banking*, 28, 64–83.

Leary, M. T., and M. R. Roberts (2014): "Do Peer Firms Affect Corporate Financial Policy?," *Journal of Finance*, 69(1), 139–178.

Lee, G., and R. W. Masulis (2009): "Seasoned equity offerings: Quality of accounting

information and expected flotation costs," *Journal of Financial Economics*, 92(3), 443–469.

Lhuissier, S., and F. Tripier (2016): "Do uncertainty shocks always matter for business cycles?," *CEPII working paper*.

Meltzer, A. H. (1963): "The demand for money: a cross-section study of business firms," *Quarterly Journal of Economics*, 77, 405–422.

Miller, M., and D. Orr (1966): "A model of the demand for money by firms," *Quarterly Journal of Economics*, 80, 413–435.

Moyen, N. (2004): "Investment-cash flow sensitivities: Constrained versus unconstrained firms," *Journal of Finance*, 59, 2061–2092.

Myers, S. C., and N. S. Majluf (1984): "Corporate financing and investment decisions when firms have information that investors do not have," *Journal of Financial Economics*, 13(2), 187–221.

Nieuwerburgh, S. V., and L. Veldkamp (2006): "Learning Asymmetries in Real Business Cycles," *Journal of Monetary Economics*, 53, 753–772.

Orlik, A., and L. Veldkamp (2015): "Understanding Uncertainty Shocks and the Role of the Black Swan," *Working paper, NYU*.

Ottonello, P., and T. Winberry (2016): "Financial Heterogeneity and the Investment Channel of Monetary Policy," *Working Paper*.

Panousi, V., and D. Papanikolaou (2012): "Investment, Idiosyncratic Risk, and Ownership," *Journal of Finance*, 67(3), 1113–1148.

Pastor, L., and R. Stambaugh (2003): "Liquidity Risk and Expected Stock Returns," *Journal of Political Economy*, 111, 642–685.

Pastor, L., and P. Veronesi (2012): "Uncertainty about Government Policy and Stock Prices," *Journal of Finance*, 67, 1219–1264.

Pinkowitz, L., R. M. Stulz, and R. Williamson (2013): "Is there a U.S. High Cash Holdings Puzzle after the Financial Crisis?," *Working Paper*.

——— (2016): "Do U.S. Firms Hold More Cash than Foreign Firms Do?," *The Review of Financial Studies*, 29(2), 309–348.

Rajan, R. G., and L. Zingales (1995): "What do we know about capital structure? Some evidence from international data," *Journal of Finance*, 50, 1421–1460.

Ramey, V., and G. Ramey (1995): "Cross-country evidence on the link between volatility and growth," *American Economic Review*, 85,5, 1138–51.

Rampini, A., and S. Viswanathan (2013): "Collateral and capital structure," *Journal of Financial Economics*, 109, 466–492.

Riddick, L. A., and T. M. Whited (2009): "The corporate propensity to save," *Journal of Finance*, 64, 1729–1766.

Rietz, T. (1988): "The equity premium: a solution," *Journal of Monetary Economics*, 22(1), 117131.

Romer, C. (1990): "The Great Crash and the Onset of the Great Depression," *Quarterly Journal of Economics*, 105(3), 597–624.

Romer, C. D., and D. H. Romer (2017): "New Evidence on the Aftermath of Financial Crises in Advanced Countries," *American Economic Review*, 107(10), 3072–3118.

Segal, G., I. Shaliastovich, and A. Yaron (2015): "Good and Bad Uncertainty: Macroeconomic and Financial Market Implications," *Journal of Financial Economics*, 117, 369–397.

Sharpe, S. A. (1994): "Financial Market Imperfections, Firm Leverage, and the Cyclicality of Employment," *American Economic Review*, 84(4), 1060–1074.

Stein, L., and E. Stone (2013): "The effect of uncertainty on investment, hiring and RD: causal evidence from equity options," *Arizona State University mimeo*.

Stock, J., and M. Watson (2012): "Disentangling the channels of the 2007-09 recession," *Brookings Papers on Economic Activity*, 1, 81–135.

Welch, I. (2004): "Capital Structure and Stock Returns," *Journal of Political Economy*, 112, 106–131.

Whited, T., and G. Wu (2006): "Financial Constraints Risk," *Review of Financial Studies*, 19, 531–559.

Table 1
Investment rate

$I_{i,t}/K_{i,t-1}$	(1) OLS Realized	(2) IV Realized	(3) IV Realized	(4) OLS Implied	(5) IV Implied	(6) IV Implied
ΔVolatility$_{i,t-1}$	-0.032***	-0.098***	-0.035***	-0.089***	-0.248***	-0.100***
	(0.002)	(0.028)	(0.013)	(0.008)	(0.059)	(0.038)
Book Leverage$_{i,t-1}$			-0.050***			-0.036***
			(0.006)			(0.007)
Stock Return$_{i,t-1}$			0.008***			0.005*
			(0.003)			(0.003)
Log Sales$_{i,t-1}$			-0.022***			-0.021***
			(0.003)			(0.004)
Return on Assets$_{i,t-1}$			0.139***			0.127***
			(0.025)			(0.034)
Tangibility$_{i,t-1}$			-0.117***			-0.127***
			(0.019)			(0.035)
Tobin's Q$_{i,t-1}$			0.049***			0.053***
			(0.005)			(0.006)
1st moment 10IV$_{i,t-1}$	No	No	Yes	No	No	Yes
Firm, time FE	Yes	Yes	Yes	Yes	Yes	Yes
SE cluster(3SIC)	Yes	Yes	Yes	Yes	Yes	Yes
Observations	124,178	28,600	28,320	26,012	17,657	17,481
F 1st st. Cragg-D		125.3	134.2		64.66	46.65
F 1st st. Kleib.-P		14.77	15.04		11.56	8.069
p-val Sargan–H J		0.807	0.992		0.373	0.740

Notes: Table presents OLS and 2SLS annual regression results of firm-level investment rate on 1-year lagged changes in firm-level volatility and lagged level of firm-level controls. Investment rate at fiscal year t is defined as I_t/K_{t-1} (capx/lagged net property plant & equipment from Compustat). Sample period is from 1963 to 2016. Specifications 1, 2, 4, and 5 are univariate, while 3 and 6 multivariate. Columns 1 and 4 are OLS while all others 2SLS. We address endogeneity concerns on firm-level volatility by instrumenting with industry-level (3SIC) non-directional exposure to 10 aggregate sources of uncertainty shocks. These include the lagged exposure to annual changes in expected volatility of energy, currencies, and 10-year treasuries (as proxied by at-the-money forward-looking implied volatilities of oil, 7 widely traded currencies, and TYVIX) and economic policy uncertainty from Baker, Bloom, and Davis (2016). Annual realized volatility is the 12-month standard deviation of daily stock returns from CRSP. Implied volatility is the annual average of daily (365-day-horizon) implied volatility of at-the-money-forward call options from OptionMetrics. Both firm and calendar-year fixed effects are included. Standard errors are clustered at the 3-digit SIC industry (in parentheses), with stronger results clustered at the firm level. To tease out the impact of 2nd moment uncertainty shocks from 1st moment aggregate shocks we also include as controls the lagged directional industry 3SIC exposure to changes in the price of each of the 10 aggregate instruments (i.e., 1st moment return shocks). These are labeled 1st moment 10IV$_{i,t-1}$. Firm-level Tobin's Q and stock return control for 1st moment effects at the firm-level. 2SLS first-stage F-statistics are Cragg-Donald (CD) for robust standard errors and Kleibergen-Paap (KP) for 3SIC clustered errors. The p-value for the Sargan-Hansen overidentification test for the validity of the instruments is also reported. Full 2SLS first stage results are discussed in Appendix section A.8. Data availability on implied volatility of treasuries and oil restrict the start of the baseline 2SLS sample to fiscal year 2005. Results are robust to dropping these instruments from the set of 10 IVs and/or using their realized volatilities to expand the sample. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1, † p<0.15. See section 2 for data details.

Table 2
Additional real quantities

	OLS Realized	IV Realized	IV Realized	OLS Implied	IV Implied	IV Implied
A: ΔIntangible Capital Investment$_{i,t}$						
ΔVolatility$_{i,t-1}$	-0.054***	-0.109***	-0.049**	-0.138***	-0.238***	-0.131**
	(0.005)	(0.030)	(0.022)	(0.015)	(0.078)	(0.066)
Observations	66,050	17,167	17,035	16,162	10,989	10,895
F 1st st. Cragg-D		90.89	89.27		36.82	32.24
F 1st st. Kleib.-P		11.97	12.65		6.483	7.704
p-val Sargan–H J		0.159	0.333		0.176	0.131
B: ΔEmployment$_{i,t}$						
ΔVolatility$_{i,t-1}$	-0.037***	-0.093**	-0.025	-0.116***	-0.292***	-0.076
	(0.003)	(0.037)	(0.038)	(0.010)	(0.088)	(0.114)
Observations	124,270	28,598	28,307	26,074	17,651	17,469
F 1st st. Cragg-D		125.3	134.3		64.82	46.67
F 1st st. Kleib.-P		14.66	14.92		11.64	8.145
p-val Sargan–H J		0.279	0.262		0.210	0.427
C: ΔCost of Goods Sold$_{i,t}$						
ΔVolatility$_{i,t-1}$	-0.054***	-0.325**	-0.195***	-0.206***	-0.978**	-0.537***
	(0.005)	(0.158)	(0.048)	(0.034)	(0.386)	(0.133)
Observations	125,498	28,652	28,361	26,135	17,681	17,498
F 1st st. Cragg-D		125.8	134.6		64.83	46.70
F 1st st. Kleib.-P		14.63	14.88		11.59	8.111
p-val Sargan–H J		0.0508	0.0039		0.142	0.0073
D: ΔSales$_{i,t}$						
ΔVolatility$_{i,t-1}$	-0.041***	-0.244***	-0.224***	-0.149***	-0.687***	-0.644**
	(0.004)	(0.086)	(0.086)	(0.017)	(0.176)	(0.249)
Observations	125,500	28,652	28,361	26,135	17,681	17,498
F 1st st. Cragg-D		125.8	134.6		64.83	46.70
F 1st st. Kleib.-P		14.63	14.88		11.59	8.111
p-val Sargan–H J		0.0138	0.0064		0.0552	0.0473

Notes: This table reports regression results of annual changes in intangible capital investment (research and development+selling, general and administrative expense from Compustat) (Panel A), changes in employment (B), changes in cost of goods sold (C), and changes in sales (D), where growth rates defined as $(x_t - x_{t-1})/(0.5 * x_t + 0.5 * x_{t-1})$. Specifications 1 through 6 follow the setup, timing, and set of controls included in the investment rate regression in Table 1. To preserve space we do not report the controls. Sample period is from 1963 to 2016. Specifications 1, 2, 4, and 5 are univariate, while 3 and 6 multivariate. Columns 1 and 4 are OLS while all others 2SLS. We address endogeneity concerns on firm-level volatility by instrumenting with industry-level (3SIC) non-directional exposure to 10 aggregate sources of uncertainty shocks. These include the lagged exposure to annual changes in expected volatility of energy, currencies, and 10-year treasuries (as proxied by at-the-money forward-looking implied volatilities of oil, 7 widely traded currencies, and TYVIX) and economic policy uncertainty from Baker, Bloom, and Davis (2016). Annual realized volatility is the 12-month standard deviation of daily stock returns from CRSP. Implied volatility is the annual average of daily (365-day-horizon) implied volatility of at-the-money-forward call options from OptionMetrics. Both firm and calendar-year fixed effects are included. Standard errors are clustered at the 3-digit SIC industry (in parentheses), with stronger results clustered at the firm level. To tease out the impact of 2nd moment uncertainty shocks from 1st moment aggregate shocks we also include as controls the lagged directional industry 3SIC exposure to changes in the price of each of the 10 aggregate instruments (i.e., 1st moment return shocks). These are labeled 1st moment 10IV$_{i,t-1}$. Firm-level Tobin's Q and stock return control for 1st moment effects at the firm-level. Data availability on implied volatility of treasuries and oil restrict the start of the baseline 2SLS sample to fiscal year 2005. Results are robust to dropping these instruments from the set of 10 IVs and/or using their realized volatilities to expand the sample. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1, † p<0.15. See section 2 for data details.

Table 3
Financial outcomes

	(1) OLS Realized	(2) IV Realized	(3) IV Realized	(4) OLS Implied	(5) IV Implied	(6) IV Implied
A: ΔPayout$_{i,t}$						
ΔVolatility$_{i,t-1}$	-0.158***	-0.553***	-0.311***	-0.499***	-1.372***	-0.700**
	(0.012)	(0.129)	(0.119)	(0.059)	(0.335)	(0.339)
Observations	125,423	28,629	28,338	26,105	17,667	17,484
F 1st st. Cragg-D		125.6	134.5		64.73	46.72
F 1st st. Kleib.-P		14.56	14.84		11.58	8.126
p-val Sargan–H J		0.501	0.884		0.994	0.967
B: ΔTotal Debt$_{i,t}$						
ΔVolatility$_{i,t-1}$	-0.079***	-0.306***	-0.191**	-0.204***	-0.809***	-0.675***
	(0.008)	(0.087)	(0.079)	(0.030)	(0.161)	(0.201)
Observations	124,602	28,477	28,304	25,959	17,556	17,459
F 1st st. Cragg-D		124.7	134.5		63.68	46.47
F 1st st. Kleib.-P		14.67	14.94		11.77	8.172
p-val Sargan–H J		0.0919	0.549		0.469	0.291
C: ΔCash holding$_{i,t}$						
ΔVolatility$_{i,t-1}$	0.030***	0.245***	0.156**	0.114***	0.743***	0.546**
	(0.009)	(0.075)	(0.079)	(0.033)	(0.179)	(0.238)
Observations	125,483	28,649	28,358	26,132	17,678	17,678
F 1st st. Cragg-D		125.8	134.6		64.86	46.73
F 1st st. Kleib.-P		14.63	14.88		11.62	8.134
p-val Sargan–H J		0.546	0.302		0.0768	0.0573

Notes: This table reports regression results of annual changes in firm payout (cash dividend + share repurchase) (Panel A), changes in total debt (B), and changes in cash holdings (cash and short-term investments) (C), where growth rates are defined as $(x_t - x_{t-1})/(0.5 * x_t + 0.5 * x_{t-1})$. Specifications 1 through 6 follow the setup, timing, and set of controls included in the investment rate regression in Table 1. To preserve space we do not report the controls. Sample period is from 1963 to 2016. Specifications 1, 2, 4, and 5 are univariate, while 3 and 6 multivariate. Columns 1 and 4 are OLS while all others 2SLS. We address endogeneity concerns on firm-level volatility by instrumenting with industry-level (3SIC) non-directional exposure to 10 aggregate sources of uncertainty shocks. These include the lagged exposure to annual changes in expected volatility of energy, currencies, and 10-year treasuries (as proxied by at-the-money forward-looking implied volatilities of oil, 7 widely traded currencies, and TYVIX) and economic policy uncertainty from Baker, Bloom, and Davis (2016). Annual realized volatility is the 12-month standard deviation of daily stock returns from CRSP. Implied volatility is the annual average of daily (365-day-horizon) implied volatility of at-the-money-forward call options from OptionMetrics. Both firm and calendar-year fixed effects are included. Standard errors are clustered at the 3-digit SIC industry (in parentheses), with stronger results clustered at the firm level. To tease out the impact of 2nd moment uncertainty shocks from 1st moment aggregate shocks we also include as controls the lagged directional industry 3SIC exposure to changes in the price of each of the 10 aggregate instruments (i.e., 1st moment return shocks). These are labeled 1st moment 10IV$_{i,t-1}$. Firm-level Tobin's Q and stock return control for 1st moment effects at the firm-level. Data availability on implied volatility of treasuries and oil restrict the start of the baseline 2SLS sample to fiscal year 2005. Results are robust to dropping these instruments from the set of 10 IVs and/or using their realized volatilities to expand the sample. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1, † p<0.15. See section 2 for data details.

Table 4
Effect of uncertainty shocks amplified by financial frictions

$I_{i,t}/K_{i,t-1}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Firm Financial Constraint $_{i,t-5}$		S&P Rating		Size&Age	WhitedWu		S&P Rating
						Placebo Tests :	$Cred_Spread_{t-3}$
$\Delta\sigma_{i,t-1}$	-0.025**	-0.033**	-0.028**	-0.025**	-0.026**	-0.028**	-0.028***
	(0.011)	(0.013)	(0.011)	(0.011)	(0.011)	(0.012)	(0.010)
$\Delta\sigma_{i,t-1}{\cdot}Cred_Spread_t$	-0.035***		-0.022**	-0.026**	-0.024**	0.002	-0.003
	(0.012)		(0.010)	(0.011)	(0.011)	(0.015)	(0.014)
$\Delta\sigma_{i,t-1}{\cdot}D^{Fin.Const}_{i,t-5}$		-0.010	-0.002	-0.003	-0.013		-0.009
		(0.010)	(0.012)	(0.013)	(0.013)		(0.011)
$\Delta\sigma_{i,t-1}{\cdot}D^{Fin.Const}_{i,t-5}{\cdot}Cred_Spread_t$			-0.019**	-0.016**	-0.008		0.012*
			(0.009)	(0.008)	(0.011)		(0.007)
Observations	28,320	28,207	25,898	25,897	24,677	28,320	25,898
F-test 1st Stage Cragg-D	61.37	66.22	28.42	26.31	26.02	60.08	29.70
F-test 1st Stage Kleib.-P.	10.13	8.906	8.001	9.071	8.162	7.636	6.048
p-value Sargan-H J	0.799	0.989	0.992	0.672	0.733	0.661	0.802
p-value $(\beta^{FC}_{\Delta\sigma} + \beta^{FC}_{CS{\cdot}\Delta\sigma}) \geqslant 0$			0.045	0.057	0.078		0.617

Notes: Table presents 2SLS annual regression results of firm-level investment rate on 1-year lagged changes in firm-level annual realized volatility of daily CRSP returns, $\Delta\sigma_{i,t-1}$, and its interaction with the year t aggregate Moody's corporate credit spread BAA-AAA, $Credit_Spread_t$, and a dummy, $D^{Fin.Constrained}_{i,t-5}$, that takes value one for firms classified as ex-ante financially constrained using information in fiscal year $t-5$, zero otherwise. The credit spread is standardized to ease interpretation of coefficients. Regression models are in Eq. (3) for columns (1,6), Eq. (5) for (2), and Eq. (4) for (3,4,5,7). Estimates on $D^{Fin.Constrained}_{i,t-5}{\cdot}Credit_Spread_t$ in columns (3,4,5,7) and $D^{Fin.Constrained}_{i,t-5}$ in (2,3,4,5,7) are not presented in the Table to preserve space. A full set of firm-level controls, 1st moment aggregate return shock controls, and both firm and year fixed effects are included (e.g., as in baseline specification (3) in Table 1), thus $Credit_Spread_t$ is collinear with the time fixed effects. Standard errors are 2SLS and in parenthesis clustered at the 3digit SIC industry. We address endogeneity concerns on firm-level volatility by instrumenting with industry-level (3SIC) non-directional exposure to 10 aggregate sources of uncertainty shocks, which include the lagged exposure to annual changes in expected volatility of energy, currencies, and 10-year treasuries (as proxied by option-implied volatilities of oil, 7 widely traded currencies, and TYVIX), and economic policy uncertainty from Baker, Bloom, and Davis (2016). Firms are either ex-ante financially constrained or unconstrained based on their constraint status in year $t-5$, as classified by: S&P credit ratings (columns 2,3,7), which follows Duchin, Ozbas, and Sensoy (2010) and consider a firm constrained if it has positive debt and no bond rating and unconstrained otherwise (which includes firms with zero debt and no debt rating), Size and Age index (SA) of Hadlock and Pierce (2010) (4), and the Whited and Wu (2006) index (5). A firm in year t is ex-ante financially constrained if at year $t-5$ is equal to or above the median constrained firm that year, unconstrained otherwise. We test the null $H_0 : (\beta^{FC}_{\Delta\sigma} + \beta^{FC}_{CS{\cdot}\Delta\sigma}) \geqslant 0$ that the *total negative effects* on investment are at least as large for unconstrained firms, against the alternative $H_a : (\beta^{FC}_{\Delta\sigma} + \beta^{FC}_{CS{\cdot}\Delta\sigma}) < 0$ that the total negative effects of uncertainty shocks are larger for ex-ante constrained firms. Columns (6) (7) perform placebo falsification tests where Moody's credit spread is shifted $t-3$ years, such that the timing of true spikes in aggregate financial frictions do not coincide with periods when firm financial constraints would likely bind the most. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1, † p<0.15.

Table 5
Robustness for effect of uncertainty shocks amplified by financial frictions

$I_{i,t}/K_{i,t-1}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Aggregate Financial	Romer&Romer (AER 2017)		Chicago Fed (NFCI)		Chicago Fed (ANFCI)		Financial Soundness:	
Conditions Index$_t$	US Financial Distress		National Fin. Conditions		Adjusted for Economic Conds.		1/(Distance to Insolvency)	
Firm Financial Constraint $_{i,t-5}$	S&P Credit Ratings (2,4,6,8)							
$\Delta\sigma_{i,t-1}$	-0.026**	-0.027**	-0.023**	-0.025**	-0.043***	-0.041***	-0.029***	-0.029***
	(0.011)	(0.011)	(0.010)	(0.011)	(0.012)	(0.012)	(0.010)	(0.011)
$\Delta\sigma_{i,t-1}{\cdot}Fin_Index_t$	-0.037***	-0.030***	-0.039***	-0.032***	-0.041**	-0.036**	-0.043***	-0.037***
	(0.012)	(0.011)	(0.011)	(0.010)	(0.016)	(0.015)	(0.012)	(0.011)
$\Delta\sigma_{i,t-1}{\cdot}D_{i,t-5}^{F.Const}$		0.002		0.003		-0.007		0.002
		(0.011)		(0.012)		(0.010)		(0.011)
$\Delta\sigma_{i,t-1}{\cdot}D_{i,t-5}^{F.Const}{\cdot}Fin_Index_t$		-0.022*		-0.020**		-0.019*		-0.018*
		(0.011)		(0.009)		(0.011)		(0.009)
Observations	25,898	25,898	25,898	25,898	25,898	25,898	25,898	25,898
F-test 1st Stage Cragg-D	49.32	23.49	56.25	26.07	33.21	16.75	59.81	29.30
F-test 1st Stage Kleib.-P.	10.79	9.122	11.15	11.02	4.234	3.354	7.256	6.031
p-value Sargan-H J	0.974	0.997	0.988	1	0.904	0.994	0.991	1
p-val $(\beta_{\Delta\sigma}^{FC}+\beta_{FI\cdot\Delta\sigma}^{FC})\geqslant 0$		0.062		0.070		0.036		0.064

Notes: Table presents 2SLS annual regression results of firm-level investment rate on 1-year lagged changes in firm-level annual realized volatility of daily CRSP returns, $\Delta\sigma_{i,t-1}$, and its interaction with different financial frictions indexes Fin_Index_t at year t the capture deterioration of aggregate financial conditions, and interaction with a firm-level dummy, $D_{i,t-5}^{Fin.Constrained}$, that takes value one for firms classified as ex-ante financially constrained using information in fiscal year $t-5$, zero otherwise. Financial frictions Fin_Index_t are proxied by the U.S financial distress measure by Romer and Romer (2017), Chicago Fed national financial conditions indexes NFCI and ANFCI, and financial soundness from Atkeson, Eisfeldt, and Weill (2017). Fin_Index_t is standardized to ease interpretation and comparison across columns of coefficients. Regression models are in Eq. (3) for columns (1,3,5,7) and Eq. (4) for (2,4,6,8). Estimates on $D_{i,t-5}^{Fin.Constrained}{\cdot}Fin_Index_t$ and $D_{i,t-5}^{Fin.Constrained}$ in columns (2,4,6,8) are not presented in the Table to preserve space. A full set of firm-level controls, 1st moment aggregate return shock controls, and both firm and year fixed effects are included (e.g., as in baseline specification (3) in Table 1), thus Fin_Index_t is collinear with the time fixed effects. Standard errors are 2SLS and in parenthesis clustered at the 3digit SIC industry. We address endogeneity concerns on firm-level volatility by instrumenting with industry-level (3SIC) non-directional exposure to 10 aggregate sources of uncertainty shocks, which include the lagged exposure to annual changes in expected volatility of energy, currencies, and 10-year treasuries (as proxied by option-implied volatilities of oil, 7 widely traded currencies, and TYVIX), and economic policy uncertainty from Baker, Bloom, and Davis (2016). Firms are either ex-ante financially constrained or unconstrained based on their constraint status in year $t-5$, as classified by: S&P credit ratings (column 2), which follows Duchin, Ozbas, and Sensoy (2010) and consider a firm constrained if it has positive debt and no bond rating and unconstrained otherwise (which includes firms with zero debt and no debt rating), Size and Age index (SA) of Hadlock and Pierce (2010) (3), and the Whited and Wu (2006) index (4). A firm in year t is ex-ante financially constrained if at year $t-5$ is equal to or above the median constrained firm that year, unconstrained otherwise. We test the null $H_0:(\beta_{\Delta\sigma}^{FC}+\beta_{FI\cdot\Delta\sigma}^{FC})\geqslant 0$ that the *total negative effects* on investment are at least as large for unconstrained firms, against the alternative $H_a:(\beta_{\Delta\sigma}^{FC}+\beta_{FI\cdot\Delta\sigma}^{FC})<0$ that the total negative effects of uncertainty shocks are larger for ex-ante constrained firms. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1, † p<0.15.

Table 6
Predetermined parameter values under baseline calibration

Description	Notation	Value	Justification
Technology			
Subjective discount factor	β	0.988	Long-run average of U.S. firm-level discount rate
Return on saving	r_n	0.01	50% of the risk-free rate (also tried 75% of the risk-free rate)
Share on capital	α	0.33	Capital share in output is one-third, labor share is two-thirds
Markup	ε	4	33% markup. With constant returns to scale yields a + b = 0.75
Wage	$\bar{w}$	1	Wage rate normalized to 1
Rate of depreciation for capital	δ	0.03	Capital depreciation rate assumed 3% per quarter
Fixed operating cost	f	0.2	Firms' average SG&A to sales ratio
Persistence of logged idiosyncratic productivity	ρ_z	0.95	Quarterly persistence of idiosyncratic productivity (Khan & Thomas 2008)
Uncertainty shock (2 state Markov)			
Conditional volatility of productivity	σ_L	0.051	Baseline uncertainty (Bloom et al 2018)
Conditional volatility in high uncertainty state	σ_H	0.209	Uncertainty shocks 4.1*baseline uncertainty (Bloom et al 2018)
Transition probability low to high uncertainty	$\pi^{\sigma}_{L,H}$	2.60%	Uncertainty shocks expected every 9.6 years (Bloom et al 2018)
Transition probability remaining in high uncertainty	$\pi^{\sigma}_{H,H}$	94.3%	Quarterly probability of remaining in high uncertainty (Bloom et al 2018)
Stochastic financing cost (2 state Markov)			
Transition probability low to high financing cost state	$\pi^{\eta}_{L,H}$	2.60%	Same as uncertainty shock (Also tried 5%)
Transition prob. remaining in high financing cost state	$\pi^{\eta}_{H,H}$	94.3%	Same as uncertainty shock (Also tried 50%)

Notes: This table presents the predetermined and the calibrated parameter values of the baseline model. Full details are in Appendix Section C.

Table 7
Model SMM estimation results

	(1)	(2)	(3)	(4)	(5)
	Data	**Baseline**	**Real only**	**Financial only**	**No frictions**
A: SMM estimated parameters					
c_k : Fixed cost of investment		0.036	0.233	0	0
		(0.012)	(0.001)		
η_L: Low external financing cost state		0.001	0	0.0009	0
		(0.000)		(0.000)	
η_H: High external financing cost state		0.456	0	0.2413	0
		(0.095)		(0.000)	
λ: Impact of uncertainty on financial cost		0.055	0	0.097	0
		(0.006)		(0.000)	
B: Data and model regression coefficients on firm uncertainty shocks $\Delta\sigma_{i,t}$					
$I_{i,t}/K_{i,t-1}$	-0.100	-0.095	-0.104	0.007	0.003
$\Delta Emploment_{i,t}$	-0.076	-0.032	-0.028	0.011	0.006
$\Delta Cash_{i,t}$	0.546	0.611	0.000	0.305	0.000
$\Delta Payout_{i,t}$	-0.700	-0.251	0.111	-0.852	-0.207
Criterion		2.001	11.175	9.770	15.270
C: Implied aggregate adjustment costs					
Real adj cost/Revenue		0.30%	0.66%	0.00%	0.00%
Financial adj cost/Revenue		0.05%	0.00%	0.01%	0.00%
Real+Financial adj cost/Revenue		0.35%	0.66%	0.01%	0.00%

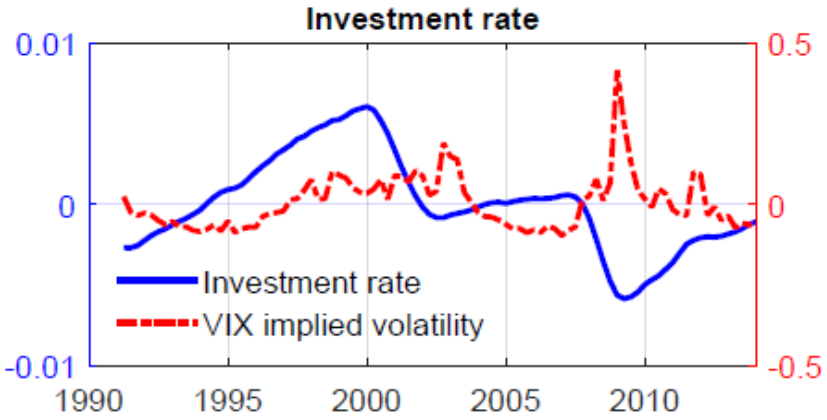
Notes: Column (1) reports the data results for investment rate, employment growth, cash growth, and equity payout growth from columns (6) of tables (1), (2), (3), respectively. Columns (2) to (5) report the estimated model parameter values and the corresponding SMM standard errors in the brackets below in the top panel, and the model counterparts from regressions using simulation data on volatility ($\sigma_{i,t}$) growth in the middle panel. The reported coefficients in the model are from simulated data with 3000 firms and 200 quarterly observations. $I_{i,t}/K_{i,t-1}$ is the investment rate, $\Delta Emplement_{i,t}$ is employment growth, $\Delta Cash_{i,t}$ is cash growth rate, and $\Delta Payout_{i,t}$ dividend payout growth in the model and cash dividend plus repurchase growth in the data. For comparability all the regressions (in the data and model) include firm and time fixed effects and all are significant at the 1% level with firm-clustered standard errors. The only difference is employment is annual in the real data (since no quarterly real employment data is available). Criterion is the error of SMM defined in Eq. (19). The bottom panel reports the aggregate real and financial adjustment costs divided the aggregate revenue for all models.

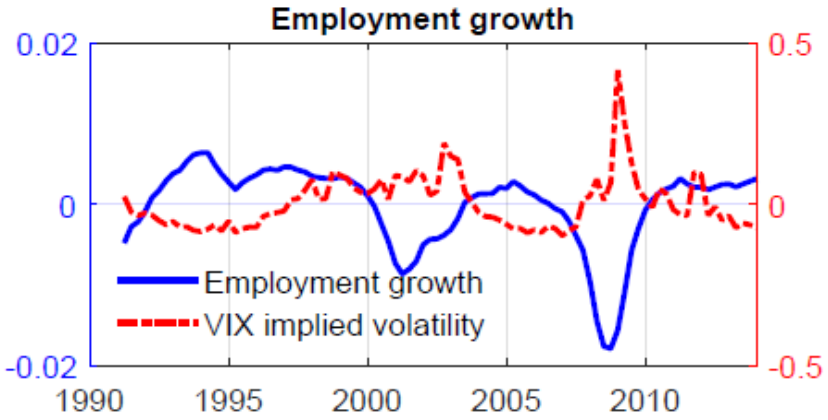
Table 8
Interactions between uncertainty shocks and financial frictions

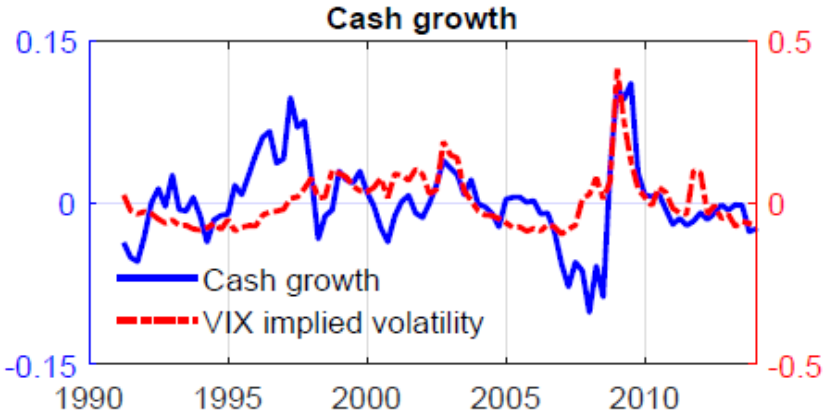
	(1) Data	(2) $\text{FinC}_{\text{Baseline}}$	(3) 0.5*$\text{FinC}_{\text{Baseline}}$	(4) 1.5*$\text{FinC}_{\text{Baseline}}$
$\Delta\sigma_{i,t}$	-0.033	-0.0693	-0.0693	-0.0693
$\Delta\sigma_{i,t}{\cdot}D_i^{Fin.Const}$	-0.010	-0.0256	-0.0124	-0.0320
Amplification effect	1.303	1.370	1.179	1.462
Firm FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes

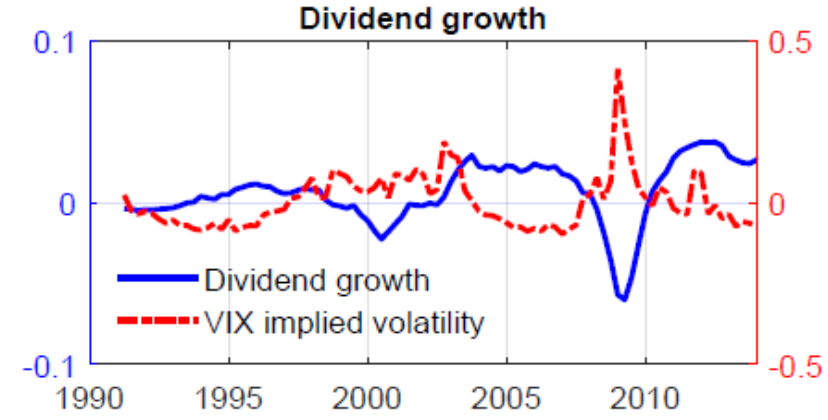
Notes: This table reports the coefficients b and c of the regression: $\frac{I_{i,t}}{K_{i,t-1}} = a + b \cdot \Delta\sigma_{i,t} + c \cdot (\Delta\sigma_{i,t} \cdot D_i^{Fin.Const}) + D_i^{Fin.Const} + \delta_i + \phi_t + \varepsilon_{i,t}$, where in the model $\Delta\sigma_{i,t}$ are firm uncertainty shocks, $D_i^{Fin.Const}$ is a dummy variable with value 1 for firms financially constrained (models with both real and financial adjustment costs) and 0 for unconstrained firms facing only real costs (real-only model without financial frictions), and fixed effects are firm δ_i and time ϕ_t. Since $D_i^{Fin.Const}$ is collinear with ϕ_t in the simulated data, it drops in the regressions. Column (1) reports instrumented 2SLS regression results from the data as reported in column (2) of Table 4 with full set of controls and both firm and year fixes effects. In column (2) financially constrained firms are from the baseline model, and in columns (3) and (4) financially constrained firms are from models with financing cost as 0.5 and 1.5 times of that of the baseline model, respectively. Unconstrained firms are from the real-only model with the same investment adjustment cost as the baseline model but with zero financing costs and stay the same in columns (3)-(5). The amplification effect is defined as the total effect of uncertainty for constrained firms relative to unconstrained, i.e., $(b + c)/b$. All model coefficients are significant at the 1% level with firm-clustered standard errors.

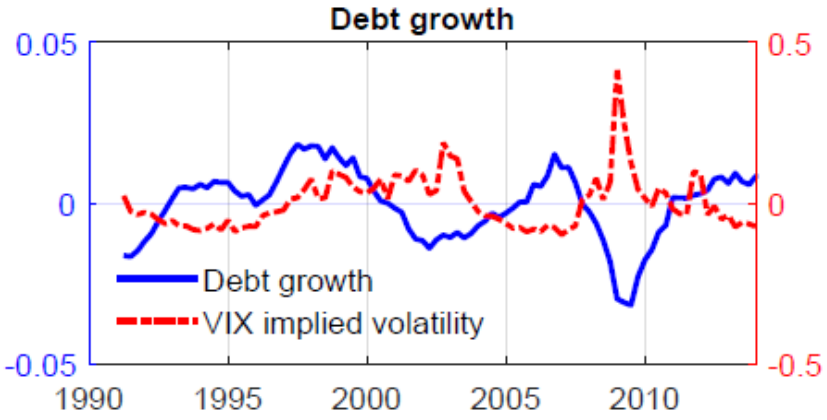
Figure 1: Uncertainty, real outcomes and financial flows





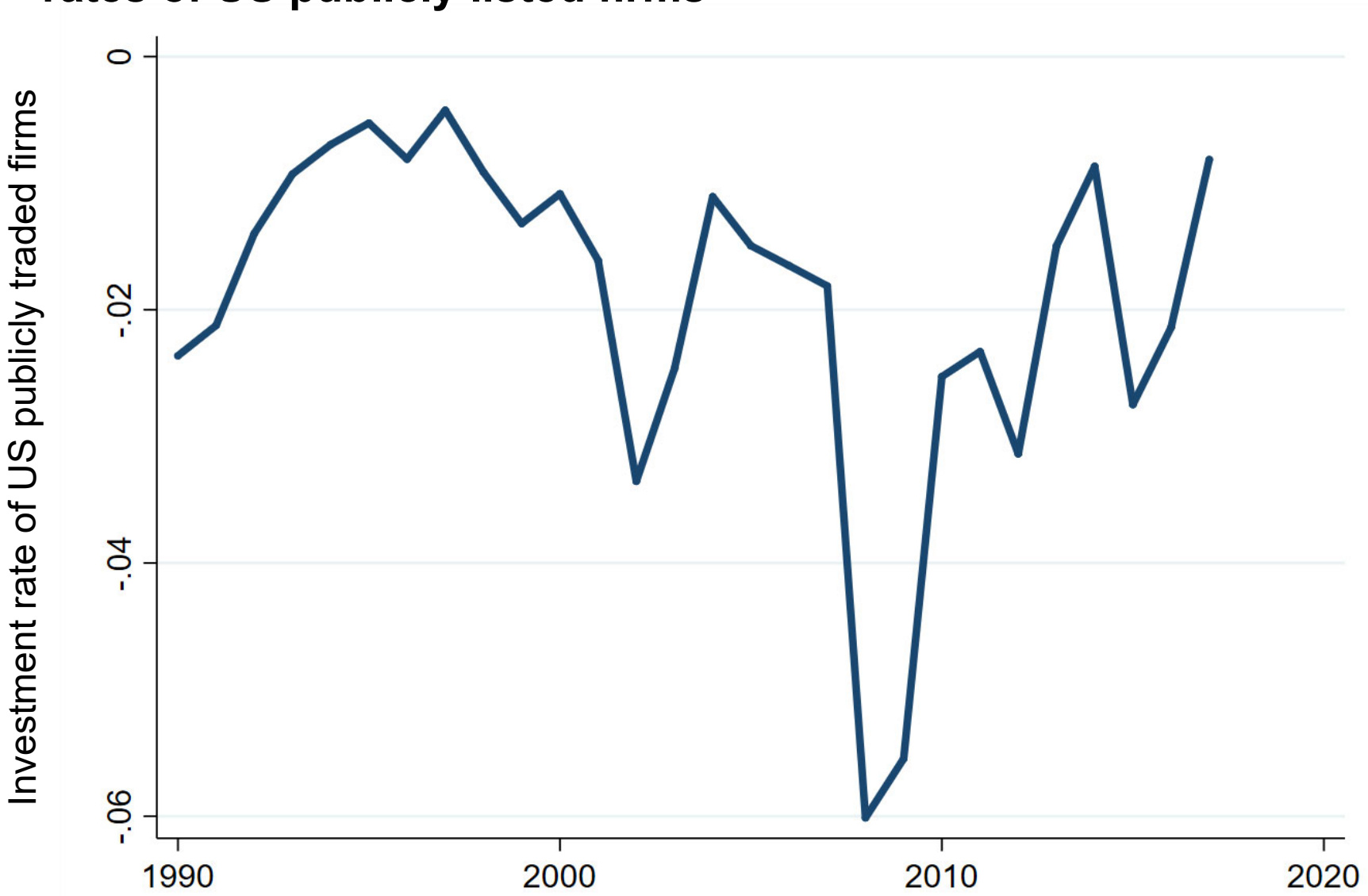






Notes: Investment rate from investment and capital data from BEA NIPS tables. Employment seasonally adjusted total private employment, BLS ID CES0500000025. Short-term debt, long-term debt, and cash from the NIPA Integrated Macroeconomic Accounts Table S.5.q nonfinancial corporate business, deflated by the CPI (NIPA table 1.1.4, line 1). Cash sum of currency and transferable deposits (line 97) and time and savings deposits (line 98). Debt is the sum of short-term debt, which includes open market paper (line 123) and short-term loans (line 127), and long-term debt which includes bonds (line 125) and mortgages (line 130). Aggregate real dividend from Shiller's webpage http://www.econ.yale.edu/~shiller/data.htm. Growth rates of variables moving average with a window of 4 quarters ahead. VIX is the implied volatility of S&P 500.

Figure 2: Implied effect of uncertainty shocks on investment rates of US publicly listed firms



Notes: Plots the average investment rate of all Compustat firms (weighted by tangible fixed assets) using the results from Table 7 column (1) where the response of firms to investment depends on both their financial constraints (the S&P credit rating) and also the credit spread (Moody's BAA-BBB spread). The response is more negative in 2008 and 2009 as more firms are financially constrained (have a lower S&P credit rating) and financial constraints (BAA-AAA spread) is higher.

Figure 3: Investment policy functions

Figure 3A: Real costs only

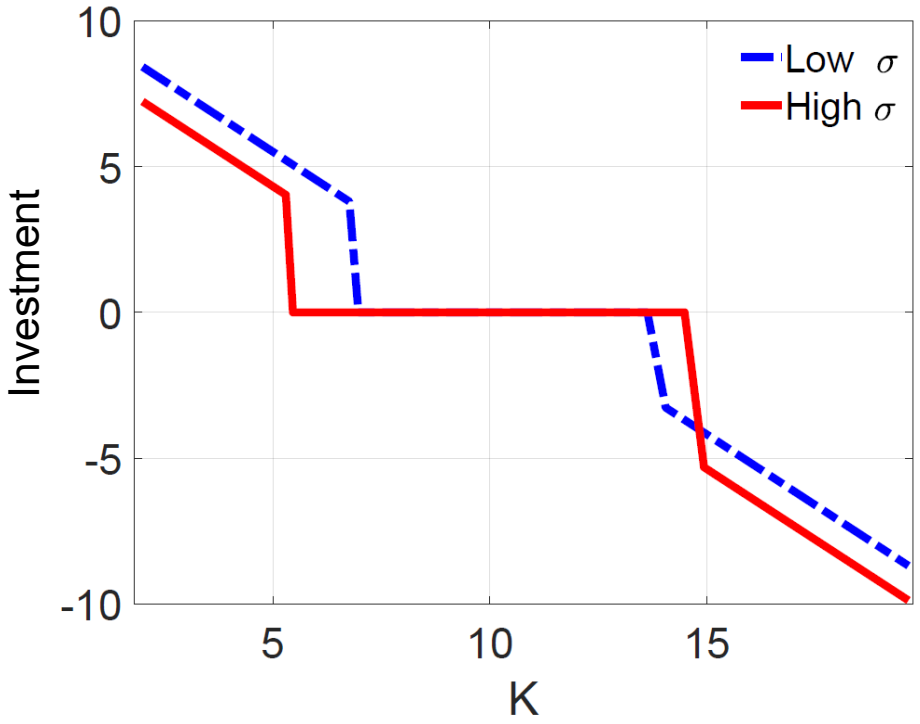
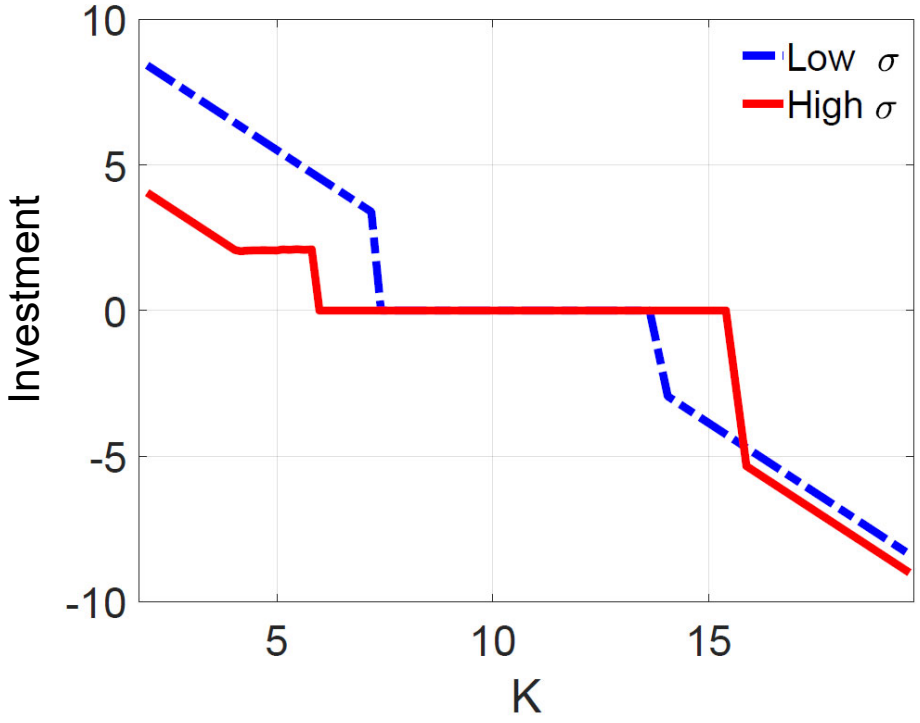
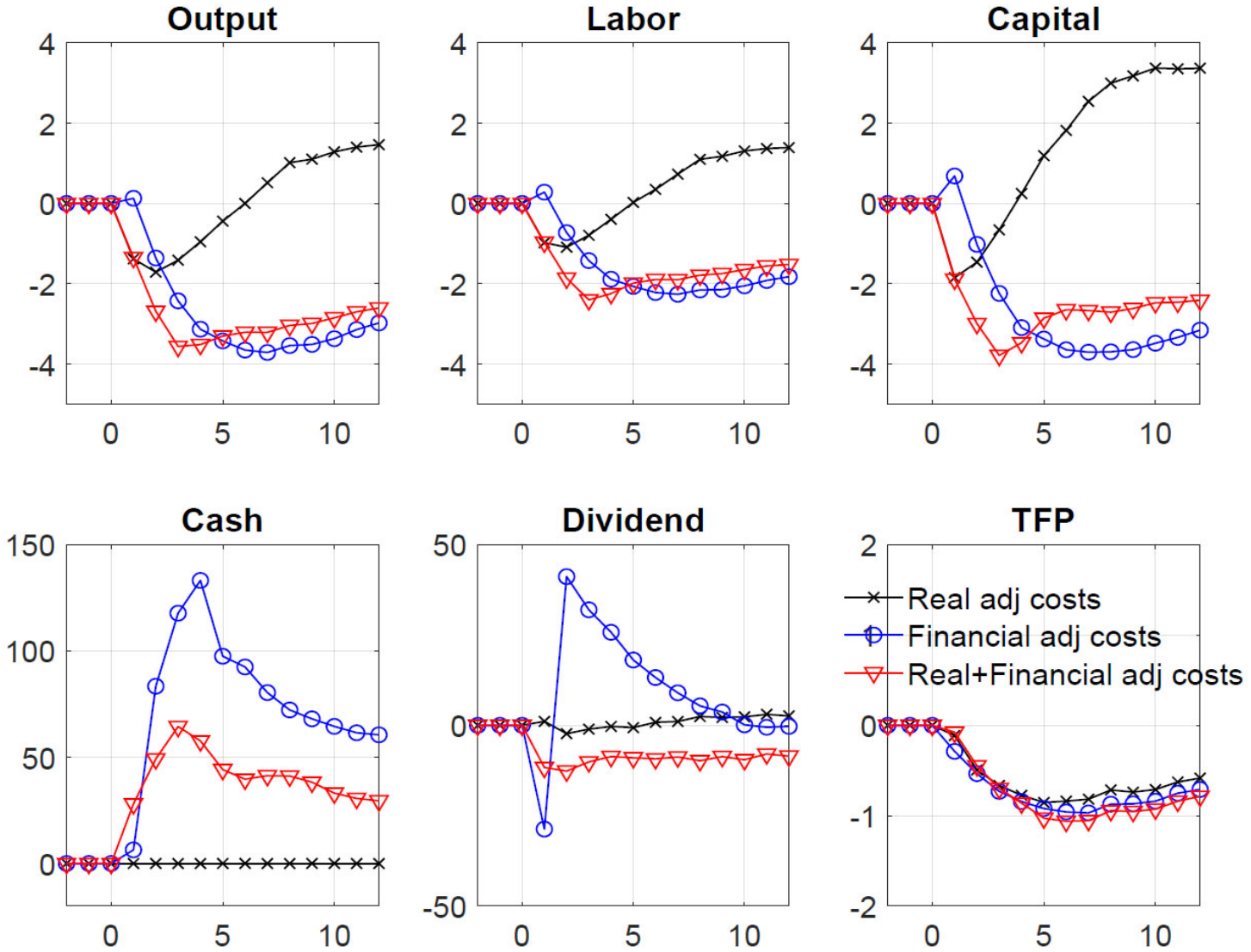


Figure 3B: Baseline: real and financial costs



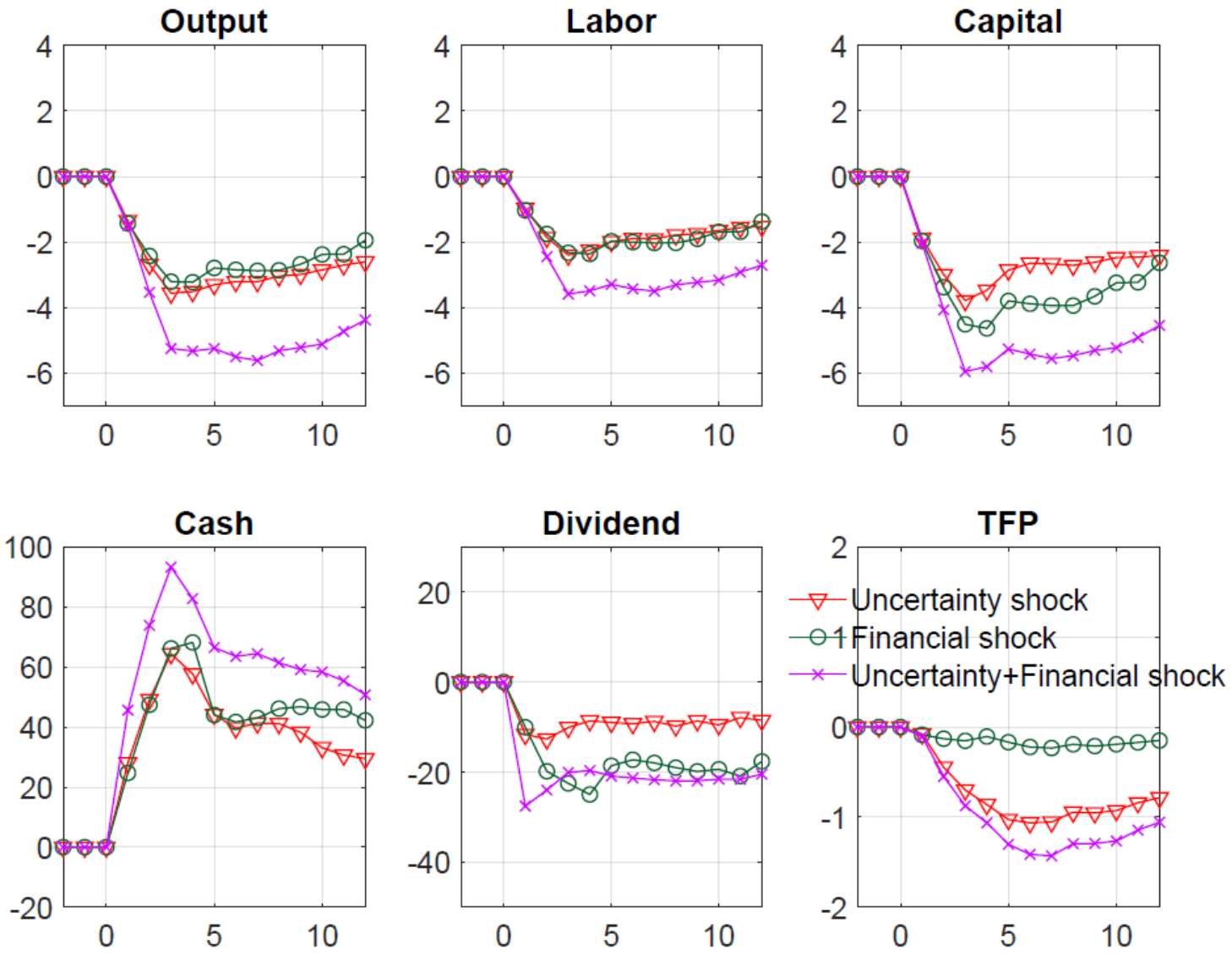
Notes: Figures 3A and 3B plot the optimal investment policies associated with low and high uncertainty shock states of the model with real investment costs only (top left) and the benchmark model (top right), respectively. In both figures, we fix the idiosyncratic productivity and cash at their median grid points and the financial shock at the low state.

Figure 4: The impact of a pure uncertainty shock



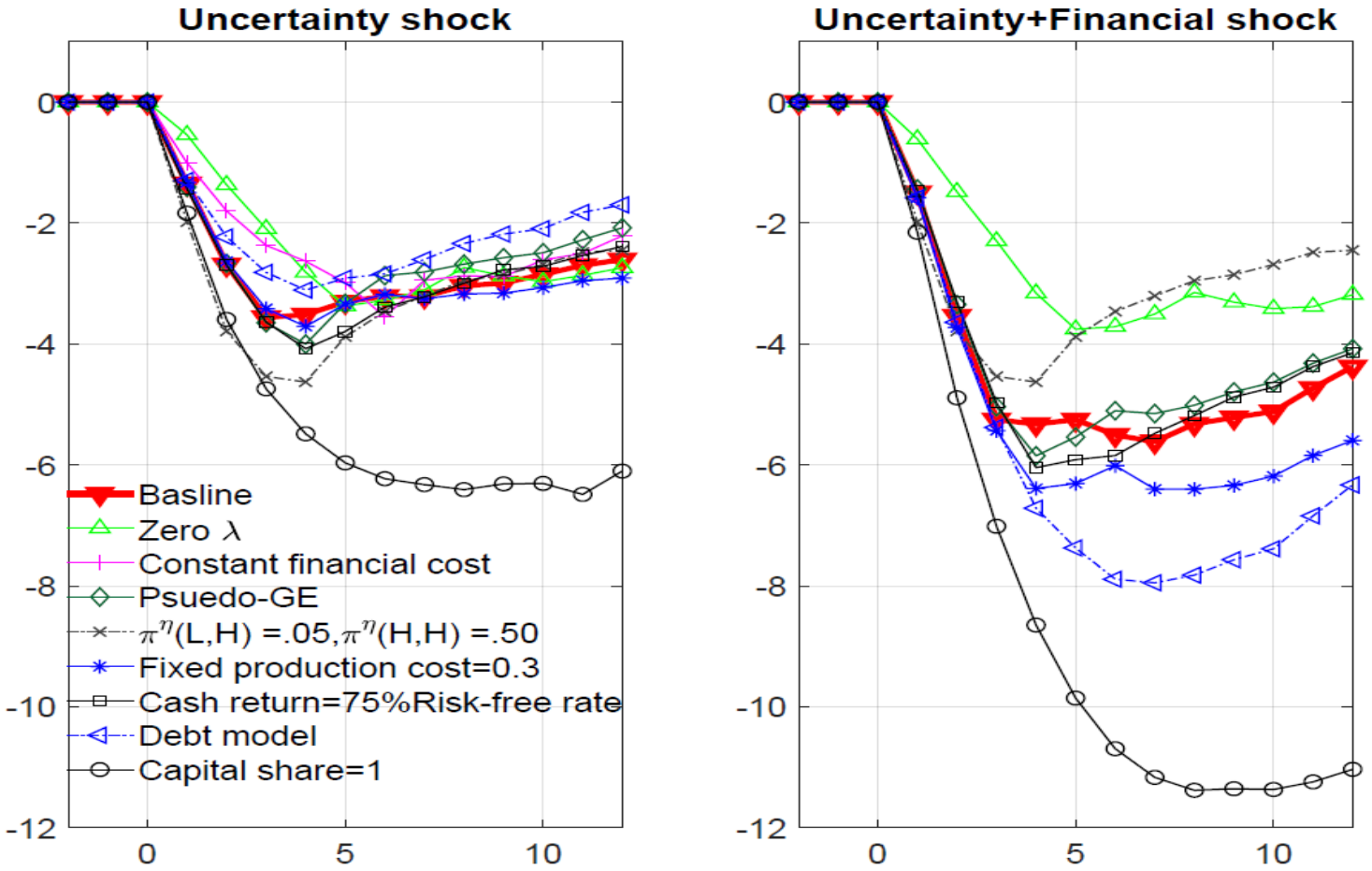
Notes: We plot the percent deviations of average output, labor, capital, cash, dividend and aggregate TFP from their values in quarter 0 of three model specifications: i) the model with real cost only (black x-mark); ii) the model with financial cost only (blue circle), and iii) the benchmark with both real and financial costs (red triangle). All plots are based on simulations of 30,000 firms of 1000-quarter length. We impose an uncertainty shock in the quarter labelled 1, allowing normal evolution of the economy afterwards.

Figure 5: The impact of uncertainty and financial shocks



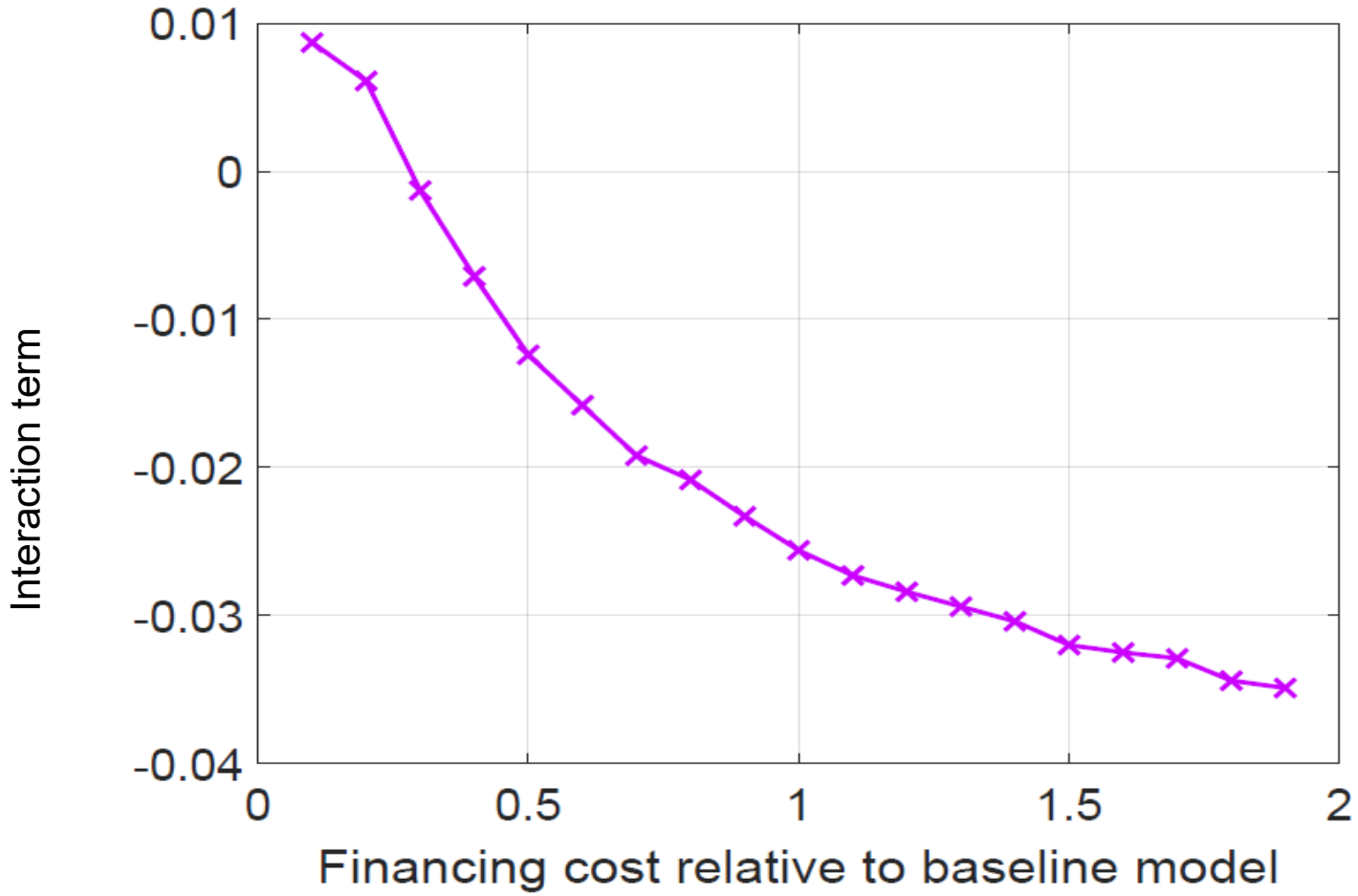
Notes: We plot the percent deviations of average output, labor, capital, cash, dividend and aggregate TFP from their values in quarter 0 of the benchmark model with both real and financial costs. All plots are based on simulations of 30,000 firms of 1000-quarter length. We impose an uncertainty shock (red triangle), a financial shock (green circle) and a combined uncertainty and financial shocks (purple x-mark) in the quarter labelled 1, allowing normal evolution of the economy afterwards.

Figure 6: Robustness check of the impact of uncertainty and financial shocks



Notes: We plot the percent deviations of average output from their values in quarter 0 of the benchmark model with both real and financial costs (red-triangle), the model with the no impact of uncertainty on financial cost (Zero lambda, green-up-triangle), the model with constant financial cost (magenta-plus), the pseudo-GE model (green-diamond), the model with a different transition matrix of financial shocks (black-dashed-cross), the model with fixed production cost at 30% (blue-star), the model with return-on-cash as 75% of risk-free rate (black-square), the model with debt and equity (blue-dashed-triangle) and the model with the capital share at 1 (black circle). All plots are based on simulations of 30,000 firms of 1000-quarter length. We impose a uncertainty shock (left panel) and a combined uncertainty and financial shocks (right panel) in the quarter labelled 1, allowing normal evolution of the economy afterwards.

Figure 7: Interaction between uncertainty shock and financing costs



Notes: We plot the coefficient *c* of the interaction term of the regression: $I_{i,t}/K_{i,t-1}=a+b*\triangle\sigma_{i,t}+c*(\triangle\sigma_{i,t} * D_i^{Fin.Const})+D_i^{Fin.Const}+\delta_i+\Phi_t+\varepsilon_{i,t}$, where $\triangle\sigma_{i,t}$ is the uncertainty shock and $D_i^{Fin.Const}$ is a dummy variable with 1 for financially constrained firms that are from models with both real and financial adjustment costs and 0 for unconstrained firms that are from the model with only real adjustment costs. The x-axis shows different models with financing cost as 0.1, 0.2,…and 1.9 (with 0.1 as an increment) times of that of the baseline model.

Appendix For Online Publication

A Data

Data used in the empirical analysis is described in detail in this section. Sources include Compustat, CRSP, OptionMetrics, Thompson Reuters Eikon, CBOE, St. Louis Fed, and Baker, Bloom, and Davis (2016). Table D.9 presents descriptive statistics of main variables used in the firm-level panel regressions. Our annual sample period begins in 1963 and ends in 2016.[41]

A.1 Company financial reports and realized stock return volatility

We draw financial information for US publicly held companies from Compustat. Sample is annual from 1963 to December 2016. We use Compustat fiscal-year annual company data from balance sheet, income statement, and cash flow statement. Financial, utilities, and public sector firms are excluded from the sample. In particular, we exclude firms with historical SIC codes in the range of 6000 to 6999, 4900 to 4999, and equal to or greater than 9000.[42] When Compustat reports more than one annual data for the same-company in a given fiscal year (e.g., when a company changes its fiscal-year end month) we drop the first chronologically dated observations and keep only the last data for that fiscal year, ensuring only one data point per firm-fiscal year. We drop any firm-year observations having zero or negative employment, total assets, and/or sales.

Our main empirical tests involve either variables in ratios, levels, and/or in changes from one fiscal year to the next. To ensure that the latter changes are indeed annual, we require a 12 month distance between fiscal-year end dates of accounting reports. Moreover, when measuring changes from one year to the next we define the growth rate as in Davis and Haltiwanger (1992), where for any variable x_t the growth rate is $\Delta x_t = (x_t - x_{t-1})/(\frac{1}{2}x_t + \frac{1}{2}x_{t-1})$, which for positive values of x_t and x_{t-1} yields growth rates bounded between -2 and 2. Moreover, whenever both x_t and x_{t-1} are zero we set the corresponding growth rate equal to zero (which avoids losing information to undefined values and because in fact the growth rate is zero in this case).

Our set of dependent variables starts with capital formation. We measure firm investment rate (implicitly the change in gross capital stock) as $\frac{CAPX_{i,t}}{K_{i,t-1}}$ where K is net property plant and equipment, and $CAPX$ is capital expenditures. We bound investment rate above at 0.5 and below at -0.10. For all other variables, we winsorize the levels, ratios, and growths every fiscal semester at the 1 and 99 percentiles. Aside from investment, we also explore additional real outcomes which include employment, EMP in Compustat , Intangible Capital, defined

[41] OLS and 2SLS regressions are run in STATA v.15 using the package REGHDFE.

[42] In general we do not use the current or "header" SIC code of a company (which is time invariant and only representative of the company's industry at the time of Compustat data download), but rather classify companies each year based on their historical industry SICH codes (i.e., standard industrial classification -historical, from Compustat), or when missing in a given year we replace it with the closest backward-looking non-missing historical code. We backfill any remaining codes using the first non-missing SICH code in the time-series. When none of the above are available we employ the firm's current (header) SIC code for all years.

as $SG\&A + R\&D$ (sales, general and administration plus research and development), cost of goods sold, $COGS$, and sales ($SALE$). Our set of financial outcomes include corporate payout defined as $Payout = DV + PRSTKC$, where DV is cash dividends and $PRSTKC$ is purchase of common and preferred stock from Compustat. Cash holdings is the level of cash and short-term investments, CHE. Total debt is $Total\ Debt = DLC + DLTT$, where DLC and $DLTT$ are short-term and long-term debt from Compustat, respectively.

Our main set of firm-level controls includes the following variables (in levels). *Stock Return* is a firm's compounded fiscal-year return, using CRSP daily returns (including dividends and adjusted for delisting, RET) within the corresponding 12-month fiscal-year period. $Tangibility_t = PPEGT/AT$, where $PPEGT$ is gross property, plant, and equipment and AT is total assets. $Book\ leverage = (DLC + DLTT)/(DLC + DLTT + CEQ)$, where CEQ is Compustat common book equity. Tobin's Q is computed as in Duchin, Ozbas, and Sensoy (2010), $Q_{i,t} = (market\ value\ of\ assets)\ /(0.9 * book\ assets + 0.1 * market\ value\ of\ assets)$, where market value of assets is ($AT + ME + CEQ - TXDB$), ME is CRSP market value of equity (i.e. stock price times shares outstanding), book assets is AT, and $TXDB$ is deferred taxes. We handle outliers in Tobin's Q by bounding Q above at 10. Return on assets, $ROA_t = EBIT/AT$, where $EBIT$ is earnings before interest and tax. We further control for firm size, defined as log $SALE$.

As for our main variable of interest firm-level uncertainty shocks, $\Delta\sigma_{i,t}$, we measure uncertainty in two ways, realized and option-implied uncertainty. Realized uncertainty is the annual volatility of the firm's realized CRSP stock return, estimated as the 12-month fiscal-year standard deviation of daily CRSP returns. We drop firm observations with less than 200 daily CRSP returns in a given fiscal year. We annualize the standard deviation by multiplying by the square root of the number of return observations (usually 252 trading days in a year when no observations are missing). Results are robust to multiplying by the square root of 252. This annualization makes the standard deviation comparable to the annual volatility implied by call options, which we describe in the next subsection. Our sample uses securities appearing on CRSP for firms listed in major US stock exchanges (EXCHCD codes 1,2, and 3 for NYSE, AMEX and the Nasdaq Stock Market (SM)) and equity shares listed as ordinary common shares (SHRCD 10 or 11).

Lastly, Moody's aggregate BAA-AAA corporate credit spread is from St. Louis Fed. We download the monthly time-series to construct annual calendar-year credit spreads using a 12-month weighted moving average of monthly values from January ($month_i = 1$) to December ($month_i = 12$), with weights $\omega_i = 1 + \frac{month_i}{10}$. Therefore, giving more weight to end-of-year monthly credit spread values. We do this because the vast majority of annual filings of publicly listed firms submitted to the U.S. Securities and Exchange Commission occur at the end of the year in December, thus better reflecting the timing of aggregate credit spreads confronted by firms each year. Using the median monthly credit spread each year gives similar results. Our annual credit spread series is standardized to ease interpretation of coefficients in the interaction regressions.

A.2 Implied volatility

Although our main measure of firm-level uncertainty is realized annual stock return volatility, we further proxy for uncertainty by using OptionMetrics' 365-day implied volatility of at-the-

money-forward call options.

OptionMetrics provides daily implied volatility from January 1996 onward for securities with exchange-traded equity options. Each security has a corresponding series of call and put options which differ in their expiration dates and strike prices. For each of these options, OptionMetrics imputes an implied volatility for each trading day using the average of the end-of-day best bid and offer price quotes. To be consistent with the annual Compustat data used throughout, our main tests focus only on 365-day implied volatility. We further restrict our analysis to call options. Note that a call option and a put option on a given underlying asset with the same strike price and expiration date have the same implied volatilities; the difference in their prices comes from the fact that interest rates and dividends affect the value of call and put options in opposite directions. Therefore, our principal proxy for uncertainty is 365-day implied volatility of at-the-money-forward call options.

A.3 Currency exchange rates and implied volatility

We use bilateral exchange rate data from the Federal Reserve Board. Although there is a large number of bilateral currencies available, we restrict our attention to 7 "major" exchange rates between the U.S. dollar of foreign currencies used by the Board in constructing the nominal and real trade-weighted U.S. dollar Index of Major Currencies[43].These include the Euro, Canadian Dollar, Japanese Yen, British Pound, Swiss Franc, Australian Dollar, and Swedish Krona. Each one of these trades widely in currency markets outside their respective home areas, and (along with the U.S. dollar) are referred to by the Board staff as major currencies. The returns to the daily currency spot prices (in excess of the daily US risk free rate) are used in the daily regression described in equation (1).

In addition to the daily exchange rate returns, our instrumental variables approach further requires measures of forward-looking implied volatility for each of the 7 currencies in equation (2). For these we use daily data on three-month implied exchange rate volatilities for each bilateral rate, downloaded from Thomson Reuters Eikon. We construct the annual industry-by-year volatilities by averaging the daily implied volatility data over the corresponding 252-day backward-looking window for each fiscal-year month-end data of a company.

A.4 10-Year US Treasury Note implied volatility

We use daily implied volatility from the Cboe/CBOT 10-year U.S. Treasury Note Volatility Index (ticker symbol: TYVIXSM), which uses Cboe's VIX methodology to measure a constant 30-day expected volatility of 10-year Treasury Note futures prices, and is calculated based on transparent pricing from CBOT's actively traded options on the T-Note futures. The TYVIX are the first exchange-traded contracts based on interest rate volatility that offer a standardized way of gaining exposure to forward implied interest rate volatility. TYVIX data are available from Q1 2003.[44]

As with exchange rates above, we construct the annual industry-by-year TYVIX volatilities by averaging the daily implied volatility data over the corresponding 252-day backward-looking

[43] See: http://www.federalreserve.gov/pubs/bulletin/2005/winter05_index.pdf .

[44] See: http://www.cboe.com/products/vix-index-volatility/volatility-on-interest-rates/cboe-cbot-10-year-u-s-treasury-note-volatility-index-tyvix .

window for each fiscal-year month-end data of a company.

A.5 Energy prices and implied volatility

We employ shocks to oil price as a general proxy for energy prices. We collect oil price and implied volatility data also from Thomson Reuters Eikon. In particular, Eikon provides daily price and 30-day implied volatility data for one-month crude oil futures. The data are from the New York Mercantile Exchange Division's light, sweet crude oil futures contract. This contract is the world's most liquid, largest-volume futures contract on a physical commodity. The contract size is 1,000 U.S. barrels and delivery occurs in Cushing, Oklahoma. Our data on oil futures implied volatility starts in Q3 2005. We extend this sample to match the start of the sample of the 10 treasuries implied volatility (TYVIX) to Q1 2003 by using the daily realized volatility (i.e., standard deviation) of oil price returns estimated over the past 252 day window. Results are robust to dropping the oil instrument altogether or using its realized volatility instead of option-implied.

As with exchange rates above, we construct our annual industry-by-year instrument for oil by averaging the daily implied volatility data for oil over the corresponding 252-day backward-looking window for each fiscal-year month-end date of a company.

A.6 Timing alignment of firm-level volatility and instruments

Most of our empirical analysis examines the effect of 1-year lagged changes in annual firm-level uncertainty $\Delta\sigma_{i,t-1}$ on the changes in both real and financial outcomes $\Delta y_{i,t}$. In defining the change in any variable x_t, growth is $\Delta x_t = (x_t - x_{t-1})/(\frac{1}{2}x_t + \frac{1}{2}x_{t-1})$. This applies to our outcomes $\Delta y_{i,t}$, lagged instruments for energy prices, exchange rates, treasuries, and policy uncertainty,$\mid \beta_{j,t-3}^{c,weighted} \mid \cdot\Delta\sigma_{t-1}^{c}$, and also our main uncertainty measures of the lagged growth in firm $i's$ realized and implied annual volatilities, $\Delta\sigma_{i,t-1}$. Given that our regressions are predictive from year $t-1$ to year t, our first-stage 2SLS regressions involve a regression of firms' lagged uncertainty shock $\Delta\sigma_{i,t-1} = (\sigma_{i,t-1} - \sigma_{i,t-2})/(\frac{1}{2}\sigma_{i,t-1} + \frac{1}{2}\sigma_{i,t-2})$ on the 10 lagged composite exposures to aggregate uncertainty shocks $z_{t-1}^{c} = \mid \beta_{j,t-3}^{c,weighted} \mid \cdot\Delta\sigma_{t-1}^{c}$ where for instrument c the growth in the lagged uncertainty shock is $\Delta\sigma_{t-1}^{c} = (\sigma_{t-1}^{c} - \sigma_{t-2}^{c})/(\frac{1}{2}\sigma_{t-1}^{c} + \frac{1}{2}\sigma_{t-2}^{c})$, and $\mid \beta_{j,t-3}^{c,weighted} \mid$ is the significance-weighted cross-industry exposure estimated 36 months prior to the firm's fiscal-year end-month dependant variable, $\Delta y_{i,t}$. Our results are robust to using the raw sensitivities,$\mid \beta_{j,t-3}^{c} \mid$, in constructing each lagged instrument $z_{t-1}^{c} = \mid \beta_{j,t-3}^{c} \mid \cdot\Delta\sigma_{t-1}^{c}$ in (2)

Taking into account that daily data on implied volatility of treasuries (TYVIX The Cboe/CBOT) starts in 1Q 2003, our main 2SLS regression sample containing the full set of 10 instruments (oil, 7 exchange rates, 10-year treasuries, and policy) effectively starts for any firm in fiscal year 2005. Our sample ends in December 2016.[45] Nonetheless, our baseline results are robust to dropping instruments from the set of 10 IVs and/or using their realized volatilities to expand the sample.

[45] Oil and 10-year treasury daily implied volatility data starts in March 2003, whereas implied volatility data on the Euro-USD bilateral exchange rate starts in 1999 and policy in 1985.

A.7 Risk adjusted returns

Using the same 10-year rolling window used in (1) we define firm daily risk-adjusted returns as the residuals of regressing firms' excess return on the daily Carhart factors:

$$r_{i,t}^{excess} = \alpha_i + \beta_{i,mkt} \cdot MKT_t + \beta_{i,HML} \cdot HML_t + \beta_{i,SMB} \cdot SMB_t + \beta_{i,UMD} \cdot UMD_t + \varepsilon_{i,t} \quad (21)$$

where $r_{i,t}^{excess}$ is firm i's daily CRSP stock return (including dividends and adjusted for delisting) in excess of the t-bill rate, MKT is the CRSP value-weighted index in excess of the risk free rate, HML is the book-to-market factor, SMB is the size factor, UMD is the momentum factor. These daily factor data are obtained from CRSP and proxy for the price of systematic risk to which firms load differentially to compensate for the risk-reward tradeoff in stock returns.[46]

Thus, by running (21) before the estimation of the sensitivities in (1) we effectively adjust firm-level returns for aggregate risk, which in turn addresses concerns over whether the sensitivities to energy, currencies, treasuries, and policy - β_j^c in equation (1)- are capturing exposures to common risk factors in stock returns rather than exposures to those 10 factors of interest for the instrumentation strategy.

A.8 2SLS first stage results

The 2SLS first stage results for investment are shown in Table D.10. Columns (1) and (2) report the first stages for the univariate IV columns (2) and (5) from table 1. We see that the F-statistics indicate a well identified first stage with respective values of 125.3 and 64.66 for the Cragg-Donald (CD) F-Statistics (robust standard-errors), and 14.77 and 11.56 for the Kleibergen-Paap (KP) F statistic (SIC-3 digit clustering). Moreover, each of the 10 instruments is individually positively correlated with firm uncertainty shocks and mostly significant at the 1%. This means that, indeed, each instrument succeeds in identifying exogenous variation in firm uncertainty shocks that arise from different unrelated sources of aggregate uncertainty shocks. Using the motivation of our instruments presented in section 2.2, exogenous variation in uncertainty shocks for firms in, say, the real manufacturing sector seems to stem not only from their exposure to oil uncertainty but at the same time also from exposure to bilateral exchange rate uncertainty affecting input and output prices for imports and exports with major developed countries and the Euro Area, and simultaneously also from exposure to political uncertainty about, say, tariff decisions made by the Executive branch and US State Department.

Moreover, we also find the Hansen over-identifying test does not reject the validity of our instruments, as shown by the p-values of the Hansen J statistic of 0.807 and 0.373 in columns (1) and (2). Thus, we fail to reject the null that our instruments are exogenous. Therefore, both the relevance and exclusion restrictions for our instruments are satisfied according to the tests.

We find similar results when we add the full set of controls, where columns (3) and (4) in Table D.10 present the first stage for the multivariate IV regressions of columns (3) and (6) from Table 1. For instance in the 1st stage of our preferred realized volatility specification in

[46] To reduce role of outliers and increase precision of industry sensitivity estimates we require firms to have a minimum of 500 daily CRSP returns in the rolling windows (i.e., about 2 years of trading return data in US public markets).

column (3), we see that each of the 10 instruments remains individually positively correlated with firm volatility shocks and significant at the 1%. Altogether, we find that even in the presence of a full set of both aggregate and firm-level controls, we see a well satisfied relevance condition, with CD F-statistics of 134.2 and 46.65, and KP F-statistics of 15.04 and 8.07, respectively, and even stronger non-rejected Sargan-Hansen validity tests, with p-values 0.992 and 0.740.

A.9 Addressing endogeneity

How do our instruments help us address endogeneity concerns in estimating the effects of firm-level uncertainty shocks? To fix ideas we think of two broad reasons for endogeneity concerns, omitted variable bias and simultaneity bias (see Jeffrey M Wooldridge (2015)). For illustration, consider the problem of some unobserved variable in the equation of investment rate of firms. Let's say this is an unobserved agency friction that affects investment and is correlated with uncertainty shocks at the firm-level (e.g., internal agency frictions between the board and the CEO of the firm lead to under-investment, while also raising uncertainty of the firm). A simple model is $\frac{I_{i,t+1}}{K_{i,t}} = \gamma_0 + \gamma_1 \Delta\sigma_{i,t} + \gamma_2 friction_{i,t} + \epsilon_{i,t+1}$. If a suitable proxy for $friction_{i,t}$ were available there is no omitted variable concern in estimating γ_1, by simply running investment rate on $\Delta\sigma_{i,t}$ and the proxy, which delivers a consistent estimator of γ_1. However, assuming the proxy is not available, then $friction_{i,t}$ is put into the error term, and we are left with the simple regression model $\frac{I_{i,t+1}}{K_{i,t}} = \gamma_0 + \gamma_1 \Delta\sigma_{i,t} + \mu_{i,t+1}$, where μ contains $friction$ and $\Delta\sigma_{i,t}$ is therefore endogenous. Of course, an OLS regression gives a biased and inconsistent estimator of γ_1. Therefore, the need for an instrument $z_{i,t}$ for $\Delta\sigma_{i,t}$.

A valid instrumental variable for $\Delta\sigma_{i,t}$ requires $Cov(z_{i,t}, \mu_{i,t+1}) = 0$ and $Cov(z_{i,t}, \Delta\sigma_{i,t}) \neq 0$, i.e., instrument exogeneity and relevance, respectively. The 1st stage F-tests of excluded instruments shown below indicate that the relevance condition is well satisfied jointly by our instruments $z_{i,t} =\mid \beta^{c,weighted}_{j,t-2} \mid \cdot \Delta\sigma^c_t$, and each of the 10 are highly positively correlated with firm uncertainty shocks at the 1% even in the presence of each other (i.e., incremental non-redundant relevance).

The exclusion restriction requires that our candidate instruments are not correlated with the unobserved $friction$ and have no direct effect on investment. In our setting, it's hard to see why firm-specific agency frictions, $friction_{i,t}$, or more broadly firm-specific unobservables that influence idiosyncratic investment rates, would be correlated with the composite terms that capture the non-directional industry-level exposures to aggregate sources of uncertainty, $z_{i,t} =\mid \beta^{c,weighted}_{j,t-2} \mid \cdot \Delta\sigma^c_t$. For instance, for the above scenario to happen the idiosyncratic agency frictions at time t would have to be correlated with either 1) shocks to the 3 month option-implied volatility of WTI crude oil futures contracts, $\Delta\sigma^{oil}_t$, and/or 2) the non-directional industry-level exposures to oil, $\mid \beta^c_{j,t-2} \mid$. The latter might be of some concern because the exposures involve the industry of each firm. However, recall that the sensitivities $\beta^c_{j,t-2}$ come from estimations done in rolling windows of a long 10 year history of daily returns at the 3-digit SIC industry levels. It's hard to see why the time t level of idiosyncratic frictions would correlate with the ex-ante determined industry-wide exposures in absolute terms, i.e., $\mid \beta^c_{j,t-2} \mid$. In addition, the timing setup of the rolling windows guarantees that the 10 year information used in estimating the exposures $\beta^c_{j,t-2}$ does not overlap with any of the dependent or independent variables at time $t+1$ and t in the investment regression. As stated above, the

exposures are ex-ante determined at the 3SIC level using information ending 3 full years prior to any of the outcome LHS variables explored in this paper, e.g., $z_{i,2007} =\mid \beta_{j,2005}^{c,weighted} \mid \cdot \Delta\sigma_{2007}^{c}$ used in instrumenting for $\Delta\sigma_{i,2007}$ in the $\frac{I_{i,2008}}{K_{i,2007}}$ regression. For the exclusion restriction not to hold, firms' $friction_{i,2007}$ would have to correlate with industry $j's$ composite term, i.e., $\mid \beta_{j,2005}^{c,weighted} \mid \cdot \Delta\sigma_{2007}^{c}$, which does not seem likely from an economic standpoint (and to the extent that we have more instruments than the endogenous firm uncertainty variable, we can test for instrument exogeneity using the Hansen over-identification test).

The concern with simultaneity bias is that, for example, firms cut investment upon higher uncertainty ($\uparrow \Delta\sigma_{i,t} \Rightarrow \downarrow \frac{I_{i,t+1}}{K_{i,t}}$), but stock return volatility might also have risen because the market saw earlier *persistent* cuts in investment for the same firm ($\downarrow \frac{I_{i,t-1}}{K_{i,t-2}} \Rightarrow \uparrow \Delta\sigma_{i,t}$), thus begging the question of whether it is uncertainty that affects investment or the opposite, or both. Therefore, a classic endogeneity problem in running the one-way OLS regression, and again the need for an instrument $z_{i,t}$ for $\Delta\sigma_{i,t}$.[47]

The industry-wide non-directional exposures, once again, help us address the endogeneity concerns here. As before a compelling story for a systematic link between the non-directional industry-level exposures $\mid \beta_{j,t-2}^{c} \mid$ and idiosyncratic investment rates – say $\frac{I_{i,t+1}}{K_{i,t}}$, $\frac{I_{i,t}}{K_{i,t-1}}$,and $\frac{I_{i,t-1}}{K_{i,t-2}}$–, is not immediate to us. Our instruments, therefore, allow us to obtain exogenous variation (explained by $z_{i,t}$) for uncertainty shocks $\Delta\sigma_{i,t}$, and thus the 2SLS estimator below gives us consistent estimates for γ_1 that are free of simultaneity bias.

A.10 Robustness: Instruments, functional form, and credit supply

This section presents robustness checks to our instrumentation strategy, checks to uncertainty functional form, and additional controls to our baseline multivariate 2SLS regressions. In practical terms, our instrumentation strategy relies on identifying cross-sectional exogenous variation in firm volatility shocks, $\Delta\sigma_{t-1}^{c}$, from non-directional exposure to 10 different aggregate volatility shocks, $z_{i,t-1} =\mid \beta_{j,t-3}^{c,weighted} \mid \cdot \Delta\sigma_{t-1}^{c}$. Even though our 1st stage results show strong relevance F-tests and high significance of individual instruments in accounting for non-redundant exogenous variation, a first concern is whether the significance of the uncertainty effects examined to this point go away once we drop any particular instrument from our instrumentation strategy. E.g, do the highly significant effects on investment and cash no longer exist once we exclude Euro-USD exchange rate volatility shocks? Moreover, a second related question is despite the obvious concerns of potential multicollinearity and noise in regression (1), whether our results depend on teasing out the most significant exposures when using the weighted estimates, $\mid \beta_{j,t-3}^{c,weighted} \mid$, instead of the raw estimates,$\mid \beta_{j,t-3}^{c} \mid$? We address these two concerns jointly in Appendix Table D.11. In particular, column (1) presents the baseline realized 2SLS results (with full set of controls) but using the raw exposures in constructing both the instrumental variables and their corresponding 1st moment aggregate controls, i.e., $z_{i,t-1} =\mid \beta_{j,t-3}^{c} \mid \cdot \Delta\sigma_{t-1}^{c}$ and first moment directional controls, $\beta_{j,t-3}^{c} \cdot r_{t-1}^{c}$. Column (1) shows that all real and financial outcomes retain their significance and sign at the 5% in responding to firm-volatility shocks. In columns (2) to (11) we examine whether

[47] One can certainly include lagged investment rates as controls in the OLS regression of investment rate on lagged uncertainty shocks, and indeed our results are robust to this, but given the codetermination of the variables it does not suffice. The estimator for uncertainty shock effects remains biased and inconsistent.

those results are robust to dropping each instrument one-by-one, starting with the implied volatility of the Canadian Dollar-USD exchange rate in column (2) and ending with the US 10 year treasury note volatility in column (11). Again, all real and financial outcomes retain their significance in response to uncertainty shocks. Moreover, the 1st stage results shown for investment at the bottom of the Table again show strong instrument relevance and validity - as indicated by the robust CD F–test always above 230.1 and the KP F-test above 33.2 in all 11 columns, while the Hansen over-identifying test does not reject in any specification with p-values in the range of 0.42 to 0.67.

Taken together, the results across all columns in Appendix Table D.11 indicate that our identification of exogenous variation in firm volatility shocks is not driven by the identification extracted from one particular instrument, but instead from the combined identification arising from energy, exchange rate, policy, and treasury uncertainty. Moreover, given the robustness of the tests the results suggest that our identification strategy will likely be useful for a wide-range of models of the causal impact of uncertainty on firm behavior.

Another concern is whether the instrumented real and financial results depend on the precise functional form used in measuring our endogenous RHS variable for uncertainty. In Appendix Table D.12 we relax our assumption on using annual changes in firm volatility, $\Delta\sigma_{i,t-1}$, and explore different reasonable transformations of this variable. In particular, columns (1) and (1A) repeat the baseline 2SLS multivariate regression results, with full set of controls, presented in columns (3) and (6) of main Tables 1, 2, and 3, which measure volatility shocks as the annual growth in CRSP realized and OptionMetrics implied volatilities, respectively. Columns (2) and (2A) present the results when using the annual growth in the square of volatility, $\Delta\sigma^2_{i,t-1}$, columns (3) and (3A) the results for volatility in levels, $\sigma_{i,t-1}$, (4) and (4A) the square of the level of volatility, $\sigma^2_{i,t-1}$, and (5) and (5A) the log of the level of volatility, $\log(\sigma_{i,t-1})$. Regardless of which specification we use to account for the endogenous uncertainty measure, we see that future real and financial variables retain their significance and sign in response to rises in uncertainty, with most results remaining significant at the 1% and 5%.

Appendix Table D.13 presents additional robustness checks for credit supply shocks, financial constraints, and 1st moment controls. First, we ask whether our results are robust to adjusting volatility shocks for financial leverage. Thus, in columns (1) and (1A) we regress all the real and financial outcomes on lagged leverage-adjusted volatility shocks, where volatility is adjusted by firm book leverage, i.e., $\sigma_{i,t-1} \cdot \frac{E_{i,t-1}}{E_{i,t-1}+D_{i,t-1}}$ where E is book equity (CEQ in Compustat) and D is total debt. Moreover, one concern could be that uncertainty reduces financial supply - for example, banks are unwilling to lend in periods of high uncertainty - which causes the results we observe. To address this we further include a variety of controls for external ratings given to firms from Standard & Poors (S&P) on their long-term obligations, an extensive set of firm-level controls for financial constraints used in the literature, and firm loadings on the aggregate market price of risk (which further controls for aggregate 1st moment effects). Again our key results remain broadly similar.

Finally, given the importance for the instrumented investment results in guiding the target moments of the model in section 4, in Appendix Table D.14 we re-examine our main investment Table 1 holding fixed the sample of firm-time observations used across all specifications (1) to (6). In particular, our sample is constrained by the availability of OptionMetrics data on firm-level implied volatility, which gives a total of 17,481 observations across all columns.

Compared to the main Table 1 the point estimates on the coefficients are largely comparable in both magnitude and statistical significance (all at the 1%). Therefore, differences in point estimates across specifications (2SLS vs OLS, univariate vs multivariate, and realized vs implied volatility shocks) are not due to differences in sample but rather differences in the underlying specifications.

A.11 Amplification effects on other outcomes

Other real outcomes. To complement the evidence of an uncertainty amplification effect through financial frictions on investment, this section examines all other real variables explored in this paper. Thus, Table D.15 examines the causal amplification effect for the growth in intangible capital investment in columns (1) and (2), cost of goods sold (3) and (4), and sales (5) and (6). As before, by running 3, we start off by asking whether the amplification effect holds on average for all firms in columns (1), (3), (5), and then use the S&P rating classifications to examine the *within-* and *cross-group* amplification effect in columns (2), (4), (6). As with capital investment, we see strong evidence that firms respond to uncertainty shocks, β_1, and more so in high financial friction years, β_2, with both coefficients significant at either the 1% or 5% for the 3 real variables. For instance, in column (1) upon an uncertainty shock firms drop their intangible capital investment, $\beta_1 = -0.036$, and further drop its rate in high friction years, $\beta_2 = -0.069$, for a total effect of uncertainty shocks of $\beta_1 + \beta_2 = -0.105\%$, and a sizable average amplification effect$= -0.105/-0.036 = 2.91$. Thus, the amplification effect is not restricted to real capital investment but also seen in intangibles. Moreover, we see strong amplifications for COGS and sales, with sizable average amplification effect$= 2.885$ and amplification effect$= 2.4$, respectively.

Dissecting the average amplification effect into groups of financially constrained and unconstrained firms, we see the following *within-constrained-group* amplification effects for intangibles $= 2.14$, cost of goods sold $= 2.87$, and sales $= 2.25$, all significant at the 1%. Moreover, in all 3 cases the *cross-group total effect* amplification effect is strong and highly significant, for intangibles $= 2$ (p-value $=0.007$), cost of goods sold $= 1.14$ (p-value $=0.031$), sales $= 1.32$ (p-value $=0.003$). Thus, providing additional strong confirmation in the data for the existence of both within group and cross-group amplifications in real variables that proxy for inputs and output of firm technology.

Financial outcomes. Finally, in Appendix Table D.16 we show the causal amplification effects for the financial variables explored in the paper. We see substantial amplification effect effects for debt, moderate ones for equity issuance, and nothing for cash holdings. Since these are constrained variables (financially constrained firms by definition will struggle to adjust their financial position) this result is not surprising, and thus the key test of the model is the amplification effect on real variables.

B Numerical algorithm

This appendix describes some of the key steps in the numerical techniques used to solve the firm's maximization problem. The full program, which runs on Matlab 64-bit, is at http://www.stanford.edu/~nbloom/.

B.1 Value function iteration

We use the value function iteration procedure to solve the firm's maximization problem numerically. We specify the two grids of 82 points for capital and 127 points for cash, respectively, with upper bounds $\bar{k}$ and $\bar{n}$ that are large enough to be non-binding. The grid for capital is constructed recursively given the pre-specified lower and upper bounds $\underline{k}$ and $\bar{k}$, following $k_i = k_{i-1}/(1-\delta)$, where $i = 1,...,s$ is the index of grids points. The grid for cash is constructed recursively using a similar approach, following $n_i = n_{i-1}/(1+r_n)$, where $i = 1,...,s$ is the index of grids points given pre-specified lower and upper bounds $\underline{n}$ and $\bar{n}$. The advantage of this construction approach is that it does not require off-grid points interpolation. For robustness check, we also construct a different grid of 60 points for cash, with upper bound $\bar{n}$ that is large enough to be non-binding. The grid for cash is constructed recursively, that is, $n_i = n_{i-1} + c_{n1}\exp(c_{n2}(i-2))$, where $i = 1,...,s$ is the index of grids points and c_{n1} and c_{n2} are two constants chosen to provide the desired number of grid points and two upper bound $\bar{n}$, given pre-specified lower bounds $\underline{n}$. The advantage of this recursive construction is that more grid points are assigned around $\underline{n}$, where the value function has most of its curvature. Linear interpolation is used to obtain optimal investment and cash holding that do not lie directly on the grid points. We find two construction approaches produce similar quantitative results.

We discretize the firm-specific productivity with two-state Markov process of time-varying conditional volatility into a 5 (productivity level) by 2 grid. In all cases, the results are robust to finer grids for the level of productivity process as well. Once the discrete state space is available, the conditional expectation can be carried out simply as a matrix multiplication. Finally, we use a simple discrete global search routine in maximizing the firm's problem.

B.2 Simulated Method of Moments Estimation

To generate the simulated data for the SMM estimation (used to create $\Psi^S(\theta)$ in Equation (19)), we simulate an economy with 3000 firms. This is run for 1000 quarters, with the first 800 quarters discarded to eliminate the effects of any assumptions on initial conditions. We use a simulated annealing algorithm for minimizing the criterion function in the estimation step in Equation (19). This starts with a predefined first. For the second guess onward it takes the best prior guess and randomizes from this to generate a new set of parameter guesses. That is, it takes the best-fit parameters and randomly "jumps off" from this point for its next guess. Over time the algorithm "cools," so that the variance of the parameter jumps falls, allowing the estimator to fine tune its parameter estimates around the global best fit. We restart the program with different initial conditions to ensure the estimator converges to the global minimum. The simulated annealing algorithm is extremely slow, which is an issue since it restricts the size of the parameter space which can be estimated. Nevertheless, we use this because it is robust to the presence of local minima and discontinuities in the criterion function across the parameter space.

To generate the standard errors for the parameter point estimates, we generate numerical derivatives of the simulation moments with respect to the parameters and weight them using the optimal weighting matrix. One practical issue with this is that the value of the numerical derivative, defined as $f'(x) = \frac{f(x+\varepsilon)-f(x)}{\varepsilon}$, is sensitive to the exact value of ε chosen. This is a common problem with calculating numerical derivatives using simulated data with underlying

discontinuities, arising, for example, from grid-point-defined value functions. To address this, we calculate four values of the numerical derivative for an ε of +1%, +2.5%, +5%, and -1% of the midpoint of the parameter space and then take the median value of these numerical derivatives. This helps to ensure that the numerical derivative is robust to outliers arising from any discontinuities in the criterion function.

C Calibration details

We discuss the calibration of some of the key baseline model parameters in detail here.

- Subjective discount factor β: We follow King and Rebelo (1999) and use the long-run average of the real stock market returns as the firm's discount rate. According to Jeremy J. Siegel (1998), the average real stock market returns is 7% in the long sample of 1802 to 1997; it is 6.6% from 1871-1925, and is 7.2% from 1926 to 1997. In the post War period, it is 6% from 1966 to 1997. However, since there is no aggregate risk in the model, subjective discount factor β also directly maps to the risk-free rate, which we use estimates of interest rates of treasury securities. The average real long-term government bond rate is 3.5% from 1802 to 1997 and is 2.8% from 1871 to 1997; while the average real T-bill rate is 2.9% from 1802 to 1997 and is 1.7% from 1871 to 1997. Given the range of estimates of the long-run average returns of stock market and the treasury securities, we choose an intermediate value of these estimates for the discount rate and set it to 5% per annum, which implies $\beta = 0.988$ per quarter.

- Return on saving r_n: Return on saving is assumed to be less than the risk-free rate because of the wedge between the two, which can be due to the tax disadvantage of carrying cash for firms or agency frictions. Unfortunately, there is no readily available value for return on cash saving. In the model it determines firms' choice on cash saving, so we set $r_n = 50\% r_f$ implying the average ratios of cash-to-total assets is 15% for firms that hold non-zero cash, which is 20% in Computat firms. We also tried $r_n = 75\% r_f$ as a robustness check.

- Markup ε : We calibrate $\varepsilon = 4$, which implies a markup of 33%, toward the upper end of the range estimates for price–cost markups in Hall (1988).

- Fixed operating cost F: We set F to be 20% of the lagged productivity in the model, consistent with the average SGA-to-sales ratio of 15% for the Compustat firms.

C.1 Model robustness

In this section we consider changes in parameter values, general equilibrium and a model with collateralized debt.

Changes in parameter values We start by re-estimating the model by changing a series of the parameter values listed in Table 7. The broad summary is that while the quantitative results vary somewhat across different models, the qualitative results are robust - uncertainty shocks lead to drops and rebounds in output, capital and labor (alongside rises in

cash and drops in equity payouts), and adding in financial adjustment costs make the impact larger and more persistent.

1. Zero-λ model. Specifically, we set the impact of uncertainty shock on financing cost, λ, to zero. This leads to a similar drop in output and similarly slow recovery as it is still expensive for constrained firms to finance investment (green line with triangles, Figure 6).

2. Constant financing cost. Next, rather than assuming stochastic financing costs, we set financing costs constant. This also leads to a slightly small drop in output but similar persistent response afterwards (purple line with plus, Figure 6).

3. Different transition matrix for financial shock. In addition, rather than set the transition probabilities of the financial shock to be the same as the uncertainty shock we set the transition probability matrix to be symmetric, i.e., $\pi^{\eta}_{L,H} = 0.05$ and $\pi^{\eta}_{H,H} = 0.50$, which implies that financial shocks expected every 5 years and that the high financing cost state is more persistent. As we see (grey-dashed line, cross) this leads to a slightly larger drop and similarly slow recovery from the uncertainty-finance shock because the finance shocks is now more persistent.

4. Larger fixed production cost. We also try increasing the fixed production cost (f) to 30% of the lagged productivity rather than 20% in the baseline calibration. We see (blue-dash line, crosses) this produces a slightly bigger drop and almost identical recovery of output to the baseline calibration from the uncertainty-finance shocks because financial constraints are not significantly loosened with a smaller fixed operating leverage.

5. Bigger capital share. Lastly, we increase the share of capital in the production function (α) to 1 rather than 1/3 in the baseline calibration. Effectively, the share of labor, the costlessly adjustable input in the baseline, is zero. This implies that all factors (capital here) are costly to adjust. We see that setting $\alpha = 1$ leads to a substantially larger drop in output to around 6.4% (3.6% in the baseline) and a slower recovery after the uncertainty-finance shock (black-dash line, right triangles).

General equilibrium Currently the model is in a partial equilibrium setting. A general equilibrium set-up would require a Krusell and Smith (1998) type of model with its additional loop and simulation to solve for prices and expectations. In prior work, for example Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018), this reduced the impact of uncertainty shocks by around 1/3 but did not radically change their character. The reason is two-fold: first, prices (interest rates and wages) do not change substantially over the cycle, and second the Ss nature of the firms' investment decision makes the policy correspondence insensitive in the short-run to price changes. However, to investigate this we do run a pseudo-GE experiment, whereby we allow prices to change by an empirically realistic amount after an uncertainty shock. In particular, we allow interest rates to be 5% lower, prices (of output and capital) 0.5% lower, and wages 0.3% lower, during periods of high uncertainty. We find broad robustness of our results on the impact of uncertainty shocks with a 20% smaller output drop and persistent recovery (green line with diamond in Figure 6).

Debt model In the baseline model we examine total external financing but do not distinguish debt vs. equity to reduce the state space of the model. We also solve and simulate a model with both debt and equity financing, and as we show in Figure 6 the results are broadly similar. Our intuition was that when debt is collateral constrained, both margins of debt and equity financing are costly for firms, hence frictions on debt and equity altogether amplify the impact of uncertainty shocks.

Specifically, at the beginning of time t, firms can issue an amount of debt, denoted as B_t, which must be repaid at the beginning of period $t+1$. The firm's ability to borrow is bounded by the limited enforceability as firms could default on their obligations. Following Hennessy and Whited (2005), we assume that the only asset available for liquidation is the physical capital K_t. In particular, we require that the liquidation value of capital is greater than or equal to the debt payment. It follows that the collateral constraint is given by

$$B_{t+1} \leq \varphi K_t. \tag{22}$$

The variable $0 < \varphi < 1$ affects the tightness of the collateral constraint, and therefore, the borrowing capacity of the firm. Due to the collateral constraint, the interest rate, denoted by r_f, is the risk-free rate.

Taxable corporate profits are equal to output less capital depreciation and interest expenses: $\Pi_t - \delta K_t - r_f B_t$. The firm's payout before equity financing cost (E_t) as operating profit minus investment in capital, cash accumulation and change in debt, less investment adjustment costs

$$E_t = (1-\tau)\,\Pi_t + \tau\delta K_t + \tau r_f B_t - I_t - H_t - G_t + B_{t+1} - (1+r_f)B_t, \tag{23}$$

in which τ is the corporate tax rate, $\tau\delta K_t$ is the depreciation tax shield, $\tau r_f B_t$ is the interest tax shield. The external equity financing cost remains the same as in the benchmark model. We set the liquidation value $\varphi = 0.85$ following Hennessy and Whited (2005) and the tax rate $\tau = 0.20$ following Gomes and Schmid (2010). We see in Figure 6 a somewhat smaller initial drop as firms can substitute debt for equity financing (blue-dashed line, triangles), and a similarly persistent impact of because of debt hangover.

Table D.9
Descriptive statistics

Variables in 2SLS	Obs.	Mean	S. Dev	P1	P10	P50	P90	P99
Dependent								
Investment Rate	125,571	0.248	0.152	0.012	0.067	0.215	0.500	0.500
ΔEmployment	125,665	0.027	0.231	-0.765	-0.192	0.022	0.258	0.744
ΔIntangible Cap. Invest.	66,975	0.077	0.198	-0.535	-0.137	0.078	0.292	0.642
ΔCost of Goods Sold	126,889	0.080	0.283	-0.929	-0.177	0.080	0.342	1.024
ΔDebt Total	125,997	0.047	0.669	-2.000	-0.514	0.000	0.739	2.000
ΔPayout	126,814	0.059	0.908	-2.000	-1.179	0.000	1.381	2.000
ΔCash Holdings	126,875	0.043	0.702	-1.727	-0.839	0.044	0.935	1.795
Independent								
ΔRealized Volatility	126,901	-0.002	0.303	-0.673	-0.376	-0.012	0.386	0.780
ΔImplied Volatility	26,743	-0.015	0.201	-0.435	-0.259	-0.026	0.248	0.519
Book Leverage	125,436	0.322	0.279	0.000	0.000	0.291	0.672	1.287
Stock Return	126,901	0.176	0.675	-0.765	-0.458	0.067	0.847	2.781
Log Sales	126,656	5.090	2.141	-0.246	2.448	5.041	7.886	9.979
Return on Assets	126,890	0.049	0.182	-0.793	-0.108	0.082	0.194	0.326
Tangibility	126,529	0.550	0.363	0.038	0.140	0.479	1.057	1.655
Tobin's Q	125,772	1.482	0.833	0.571	0.791	1.215	2.539	4.690
Instruments								
Exposure ΔVol Cad	54,127	3e-04	0.006	-0.011	-0.001	0.000	0.001	0.015
Exposure ΔVol Euro	41,750	5e-05	0.010	-0.028	-0.003	0.000	0.001	0.040
Exposure ΔVol Jpy	54,127	-2e-04	0.003	-0.009	-0.001	0.000	0.000	0.009
Exposure ΔVol Aud	54,127	-1e-04	0.006	-0.021	-0.004	0.000	0.002	0.020
Exposure ΔVol Sek	45,141	5e-04	0.008	-0.019	-0.003	0.000	0.001	0.037
Exposure ΔVol Chf	54,127	-6e-06	0.008	-0.018	-0.002	0.000	0.000	0.016
Exposure ΔVol Gbp	54,127	-9e-05	0.004	-0.013	0.000	0.000	0.000	0.012
Exposure ΔVol Oil	29,212	-7e-06	0.011	-0.042	-0.001	0.000	0.001	0.043
Exposure ΔVol Policy	54,127	-3e-08	2e-05	-5e-05	0.000	0.000	0.000	4e-05
Expos. ΔVol Treasury	29,212	-0.310	7.218	-25.880	-2.006	0.000	0.473	22.850

Notes: This table presents summary statistics of all main variables used in the empirical regression analysis. Sample period is annual from 1963 to 2016. Notation Δx stands for growth rate of variable x, defined as $(x_t - x_{t-1})/(0.5 * x_t + 0.5 * x_{t-1})$, standard deviation is S. Dev., while. P1, P10, P50, P90 and P99 stand for the 1, 10, 50, 90 and 99 percentiles, respectively. Data sources include CRSP, Compustat, OptionMetrics, Thomson Reuters Eikon, CBOE, St. Louis Fed, and Baker, Bloom, and Davis (2016). See sections 2 and 3 for the details on the construction of variables.

Table D.10
Investment rate - 2SLS 1st stage results

Specification:	Univariate		Multivariate	
Set-up: ΔVolatility$_{i,t-1}$	Realized	Implied	Realized	Implied
Exposure ΔVol Cad$_{i,t-1}$	3.179***	1.092**	2.465***	0.608
	(0.832)	(0.475)	(0.705)	(0.427)
Exposure ΔVol Euro$_{i,t-1}$	1.401***	0.651***	1.304***	0.470**
	(0.317)	(0.207)	(0.313)	(0.201)
Exposure ΔVol Jpy$_{i,t-1}$	2.731***	0.262	2.756***	0.282
	(0.972)	(0.748)	(0.931)	(0.693)
Exposure ΔVol Aud$_{i,t-1}$	4.402***	1.119***	4.989***	1.212***
	(0.616)	(0.320)	(0.633)	(0.304)
Exposure ΔVol Sek$_{i,t-1}$	3.176***	1.022***	3.524***	1.222***
	(0.520)	(0.318)	(0.579)	(0.317)
Exposure ΔVol Chf$_{i,t-1}$	1.987***	1.260***	2.078***	1.253***
	(0.429)	(0.271)	(0.495)	(0.313)
Exposure ΔVol Gbp$_{i,t-1}$	2.783***	1.328***	2.726***	1.339***
	(0.549)	(0.426)	(0.523)	(0.420)
Exposure ΔVol Policy$_{i,t-1}$	607.425***	170.390*	597.889***	161.531*
	(166.863)	(99.606)	(143.295)	(83.179)
Expos. ΔVol Treasury$_{i,t-1}$‡	2.648***	1.261***	2.527***	1.079***
	(0.452)	(0.261	(0.394)	(0.217)
Exposure ΔVol Oil$_{i,t-1}$	3.111***	1.865***	4.125***	1.708***
	(0.362)	(0.202)	(0.570)	(0.274)
Observations	28,600	17,657	28,320	17,481
F-test 1st stage Cragg-Donald	125.3	64.66	134.2	46.65
F-test 1st stage Kleibergen-Paap	14.77	11.56	15.04	8.069
p-value Hansen-Sargan J	0.807	0.373	0.992	0.740

Notes: Table presents the 2SLS first stage regression results of the excluded instruments used in firm-level investment rate on 1-year lagged changes in firm-level volatility and lagged level of firm-level controls. Columns 1 and 2 are the first stage results for the univariate specifications (3) and (6) in Table 1, while columns 3 and 4 are the multivariate first stage results of specifications (3) and (6). We address endogeneity concerns on firm-level volatility by instrumenting with industry-level (3SIC) non-directional exposure to 10 aggregate sources of uncertainty shocks. These include the lagged exposure to annual changes in expected volatility of energy, currencies, and 10-year treasuries (as proxied by at-the-money forward-looking implied volatilities of oil, 7 widely traded currencies, and TYVIX) and economic policy uncertainty from Baker, Bloom, and Davis (2016). Annual realized volatility is the 12-month standard deviation of daily stock returns from CRSP. Implied volatility is the annual average of daily (365-day-horizon) implied volatility of at-the-money-forward call options from OptionMetrics. Both firm and calendar-year fixed effects are included. Standard errors are clustered at the 3-digit SIC industry, with stronger results clustered at the firm level. To tease out the impact of 2nd moment uncertainty shocks from 1st moment aggregate shocks we also include as controls the lagged directional industry 3SIC exposure to changes in the price of each of the 10 aggregate instruments (i.e., 1st moment return shocks). These are labeled 1st moment 10IV$_{i,t-1}$. Firm-level Tobin's Q and stock return control for 1st moment effects at the firm-level. Data availability on implied volatility of treasuries and oil restrict the start of the baseline 2SLS sample to fiscal year 2005. Results are robust to dropping these instruments from the set of 10 IVs and/or using their realized volatilies to expand the sample. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1, † p<0.15. See section 2 for data details.

Table D.11
2SLS Sensitivity to individual instruments. Effect of uncertainty is not dependent on a given instrument

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
IV Dropped	None	Cad	Euro	Jpy	Aud	Sek	Chf	Gbp	Policy	Oil	Treas.
Real Variables											
$I_{i,t}/K_{i,t-1}$	-0.016**	-0.016**	-0.015**	-0.015*	-0.015*	-0.018**	-0.017*	-0.016**	-0.014*	-0.013†	-0.014*
ΔIntang.$_{i,t}$	-0.033**	-0.031**	-0.034**	-0.033**	-0.035**	-0.031**	-0.032*	-0.032**	-0.032**	-0.026*	-0.035**
ΔEmp$_{i,t}$	0.006	0.006	0.003	0.009	0.006	0.003	0.007	0.007	0.008	0.014	0.007
ΔCOGS$_{i,t}$	-0.153***	-0.151***	-0.143***	-0.167***	-0.172***	-0.178***	-0.156***	-0.152***	-0.152***	-0.123***	-0.179***
ΔSales$_{i,t}$	-0.146***	-0.145***	-0.140***	-0.137***	-0.155***	-0.167***	-0.157***	-0.144***	-0.145***	-0.106***	-0.154***
Financial Variables											
ΔDebt Total$_{i,t}$	-0.211***	-0.208***	-0.210***	-0.210***	-0.237***	-0.225***	-0.196***	-0.210***	-0.206***	-0.211***	-0.210***
ΔPayout$_{i,t}$	-0.317***	-0.325***	-0.317***	-0.314***	-0.341***	-0.298***	-0.298***	-0.320***	-0.306***	-0.320***	-0.297***
ΔCash $_{i,t}$	0.176**	0.178**	0.171**	0.178**	0.198**	0.197**	0.142*	0.173**	0.177**	0.190**	0.183**
Firm controls$_{i,t-1}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
1st moment 10IV$_{i,t-1}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm, time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster(3SIC)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Investment Rate Stats											
Observations	28,320	28,320	28,320	28,320	28,320	28,320	28,320	28,320	28,320	28,320	28,320
F-test Cragg-D	230.1	254.9	249.3	251.2	242.3	238	240.5	254.6	252.1	243.6	240.3
F-test Kleib.-P.	33.80	33.92	37.86	36.04	26.95	31.20	30.92	31.69	37.82	32.79	36.28
p-val Sargan-H J	0.522	0.422	0.424	0.433	0.475	0.676	0.466	0.421	0.639	0.507	0.657

Notes: This table presents 2SLS robustness tests to our instrumentation strategy for main real and financial outcome results (with full set of controls) presented in column (3) of Tables 1, 2, and 3. In column (1) we present the baseline 2SLS multivariate results that instruments firm-realized volatility shocks using all 10 instruments but each one constructed using the *raw non-significance adjusted* industry 3SIC exposures estimated in regression (1). Columns (2 to 11) examine the results when we further drop individual instruments one at a time from the full set of 10 instruments. The statistics under "Investment Rate Stats" correspond to the 1st stage results of the multivariate 2SLS regression of investment rate. The 1st Stage statistics for other real and financial estimations are largely comparable to their benchmark specifications with the full set of instruments. Firm and calendar-year fixed effects are included. Standard errors clustered at the 3 digit SIC industry. To tease out the impact of 2nd moment uncertainty shocks from 1st moment aggregate shocks we also include as controls the lagged directional industry 3SIC exposure to changes in the price of each of the 10 aggregate instruments (i.e., 1st moment return shocks). These are labeled 1st moment 10IV$_{i,t-1}$. Firm-level Tobin's Q and stock return control for 1st moment effects at the firm-level. Data availability on implied volatility of treasuries and oil restrict the start of the baseline 2SLS sample to fiscal year 2005. Results are robust to dropping these instruments from the set of 10 IVs and/or using their realized volatilies to expand the sample. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1, † p<0.15. See section 2 for data details.

Table D.12
2SLS robustness to different functional forms of measuring uncertainty effects

	(1)	(2)	(3)	(4)	(5)	(1A)	(2A)	(3A)	(4A)	(5A)
Firm-level Volatility	$\Delta\sigma_{i,t-1}$	$\Delta\sigma^2_{i,t-1}$	$\sigma_{i,t-1}$	$\sigma^2_{i,t-1}$	$log(\sigma_{i,t-1})$	$\Delta\sigma_{i,t-1}$	$\Delta\sigma^2_{i,t-1}$	$\sigma_{i,t-1}$	$\sigma^2_{i,t-1}$	$log(\sigma_{i,t-1})$
Volatility source	Realized	Realized	Realized	Realized	Realized	Implied	Implied	Implied	Implied	Implied
Real Variables										
$I_{i,t}/K_{i,t-1}$	-0.035***	-0.019***	-0.087***	-0.059***	-0.054***	-0.100***	-0.052***	-0.321*	-0.319*	-0.137**
ΔIntang.$_{i,t}$	-0.049**	-0.027**	-0.134**	-0.086**	-0.084**	-0.131**	-0.068**	-0.672**	-0.676**	-0.270**
ΔEmp$_{i,t}$	-0.025	-0.013	-0.081	-0.055	-0.049	-0.076	-0.038	-0.472	-0.503	-0.198
ΔCOGS$_{i,t}$	-0.195***	-0.104***	-0.529***	-0.354***	-0.323***	-0.537***	-0.278***	-2.566***	-2.747***	-1.061***
ΔSales$_{i,t}$	-0.224***	-0.119**	-0.612***	-0.408***	-0.375***	-0.644**	-0.333**	-2.974***	-3.204**	-1.220***
Financial Variables										
ΔDebt Total$_{i,t}$	-0.191**	-0.102**	-0.487***	-0.327**	-0.308***	-0.675***	-0.348***	-2.651***	-2.526***	-1.192***
ΔPayout$_{i,t}$	-0.311***	-0.170***	-0.718**	-0.495**	-0.444**	-0.700**	-0.364**	-2.422**	-2.581**	-0.974**
ΔCash $_{i,t}$	0.156**	0.085**	0.333*	0.221*	0.211*	0.546**	0.283**	1.412*	1.396†	0.583†
Firm controls$_{i,t-1}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
1st moment 10IV$_{i,t-1}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm, time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster(3SIC)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Investment Rate Stats										
Observations	28,320	28,320	28,320	28,320	28,320	17,481	17,481	18,703	18,703	18,703
F-test Cragg-D	134.2	130.6	77.63	41.38	82	46.65	46.55	11.99	6.293	16.43
F-test Kleib.-P.	15.04	14.72	12.65	10.43	10.96	8.069	8.181	4.994	3.540	5.520
p-val Sargan-H J	0.992	0.990	0.997	0.995	0.997	0.740	0.743	0.588	0.544	0.573

Notes: This table presents 2SLS multivariate regression results of real and financial outcome variables on different functional forms of lagged firm-level volatility. Columns (1) and (1A) are the baseline 2SLS multivariate regressions, with full set of controls, presented in columns (3) and (6) of main Tables 1, 2, and 3, which measure volatility shocks using the annual growth in CRSP realized and OptionMetrics implied firm-level volatility, respectively. Columns (2) and (2A) use the annual growth in the square of volatility. Columns (3) and (3A) the level of volatility, (4) and (4A) the square of volatility, and (5) and (5A) the log of volatility. All specifications address endogeneity concerns on firm-level volatility by instrumenting with industry-level (3SIC) non-directional exposure to 10 aggregate sources of uncertainty shocks. The statistics under "Investment Rate Stats" correspond to the 2SLS 1st stage of firm-level investment rates on the different proxies for uncertainty. 1st Stage statistics for other real and financial estimations are largely comparable to their benchmark specifications. Firm and calendar-year fixed effects are included. Standard errors clustered at the 3 digit SIC industry. To tease out the impact of 2nd moment uncertainty shocks from 1st moment aggregate shocks we also include as controls the lagged directional industry 3SIC exposure to changes in the price of each of the 10 aggregate instruments (i.e., 1st moment return shocks). These are labeled 1st moment 10IV$_{i,t-1}$. Firm-level Tobin's Q and stock return control for 1st moment effects at the firm-level. Data availability on implied volatility of treasuries and oil restrict the start of the baseline 2SLS sample to fiscal year 2005. Results are robust to dropping these instruments from the set of 10 IVs and/or using their realized volatilies to expand the sample. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1, † p<0.15. See section 2 for data details.

Table D.13
2SLS Robustness tests: leverage-adjusted volatility and additional controls

Volatility Instrumented	(1) Realized	(2) Realized	(3) Realized	(4) Realized	(5) Realized	(1A) Implied	(2A) Implied	(3A) Implied	(4A) Implied	(5A) Implied
Real Variables										
$I_{i,t}/K_{i,t-1}$	-0.040**	-0.035***	-0.037***	-0.036***	-0.037***	-0.096†	-0.098***	-0.104**	-0.104***	-0.104***
ΔIntangible Cap. Invest.$_{i,t}$	-0.055**	-0.047**	-0.046**	-0.047**	-0.042**	-0.147*	-0.123*	-0.128*	-0.122*	-0.109*
ΔEmployment$_{i,t}$	-0.017	-0.023	-0.028	-0.026	-0.026	0.062	-0.069	-0.081	-0.078	-0.073
ΔCOGS$_{i,t}$	-0.208***	-0.191***	-0.191***	-0.194***	-0.186***	-0.436**	-0.513***	-0.523***	-0.528***	-0.491***
ΔSales$_{i,t}$	-0.233**	-0.217**	-0.216**	-0.224***	-0.213***	-0.425*	-0.607**	-0.631***	-0.641***	-0.592***
Financial Variables										
ΔDebt Total$_{i,t}$	-0.192*	-0.190**	-0.192**	-0.190**	-0.189**	-0.789**	-0.666***	-0.682***	-0.669***	-0.666***
ΔPayout$_{i,t}$	-0.365**	-0.296**	-0.308***	-0.312***	-0.296***	-1.080*	-0.663**	-0.732**	-0.682**	-0.682**
ΔCash Holdings$_{i,t}$	0.183**	0.153**	0.145*	0.154*	0.144*	0.751*	0.563**	0.568**	0.544**	0.584***
Firm-level controls$_{i,t-1}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Leverage-adjusted ΔVolatility$_{i,t-1}$	Yes					Yes				
Covariance w/ market$_{i,t-1}$		Yes			Yes		Yes			Yes
Financial constraint indexes$_{i,t-1}$			Yes		Yes			Yes		Yes
S&P credit ratings$_{i,t-1}$				Yes	Yes				Yes	Yes
1st moment controls 10 IV$_{i,t-1}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm, time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE clustering (3SIC industry)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Investment Rate Stats										
Observations	28,266	28,320	28,235	28,320	28,235	17,448	17,481	17,433	17,481	17,433
F 1st stage Cragg-Donald Wald	72.89	142.1	133.5	134.2	141.4	9.854	50.75	46.33	47.54	51.37
F 1st stage Kleibergen-Paap Wald	10.63	16.62	14.92	15.10	16.37	3.555	9.289	8.209	8.413	9.766
p-val Sargan–Hansen J Chi-sq	0.959	0.992	0.991	0.991	0.988	0.455	0.732	0.740	0.718	0.702

Notes: This table presents 2SLS robustness results for main real and financial outcome specifications examined in columns (3 and 6) of Tables 1, 2, and 3. All specifications include full set of controls. In columns (1) and (1A) we investigate whether the results are robust to adjusting volatility by firm leverage, i.e., $\sigma_{i,t} \cdot \frac{E_{i,t}}{E_{i,t}+D_{i,t}}$ where E is book equity and D is total debt. Additional controls include: covariance w/ market, which adds firm lagged CAPM beta to control for firm loading on the market price of risk (e.g., control for 1st moment effects), financial constraint indexes, which add a set of 6 lagged firm-level controls for firm financial constraints. These include the lagged Whited-Wu index, lagged SA index of Hadlock and Pierce (2010), the Kaplan-Zingales index, reciprocal of total assets, reciprocal of employees, and reciprocal of age. The S&P credit ratings column further adds a full set of dummies based on every possible credit rating category given by S&P on long-term debt. Omitted dummy is for no credit ratings. To tease out the impact of 2nd moment uncertainty shocks from 1st moment aggregate shocks we also include as controls the lagged industry 3SIC exposure to changes in the price of each of the 10 aggregate instruments (i.e., 1st moment return shocks). These are labeled 1st moment 10IV$_{i,t-1}$. Firm and calendar-year fixed effects are included. Standard errors clustered at the 3-digit SIC industry. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1, † p<0.15. Sample is from 2005 to December 2016. Standard errors are in parentheses. See section 2 for data details.

Table D.14
Robustness for Investment rate, using same panel across specifications

$I_{i,t}/K_{i,t-1}$	(1) OLS Realized	(2) IV Realized	(3) IV Realized	(4) OLS Implied	(5) IV Implied	(6) IV Implied
ΔVolatility$_{i,t-1}$	-0.033***	-0.103***	-0.039***	-0.080***	-0.250***	-0.100***
	(0.007)	(0.032)	(0.014)	(0.010)	(0.061)	(0.038)
Book Leverage$_{i,t-1}$			-0.040***			-0.036***
			(0.006)			(0.007)
Stock Return$_{i,t-1}$			0.006**			0.005*
			(0.003)			(0.003)
Log Sales$_{i,t-1}$			-0.022***			-0.021***
			(0.004)			(0.004)
Return on Assets$_{i,t-1}$			0.134***			0.127***
			(0.034)			(0.034)
Tangibility$_{i,t-1}$			-0.131***			-0.127***
			(0.034)			(0.035)
Tobin's Q$_{i,t-1}$			0.055***			0.053***
			(0.007)			(0.006)
1st moment 10IV$_{i,t-1}$	No	No	Yes	No	No	Yes
Firm, time FE	Yes	Yes	Yes	Yes	Yes	Yes
SE cluster(3SIC)	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,481	17,481	17,481	17,481	17,481	17,481
F 1st st. Cragg-D		98.73	104.3		64.27	46.65
F 1st st. Kleib.-P		11.40	11.93		11.72	8.069
p-val Sargan–H J		0.404	0.721		0.373	0.740

Notes: This table presents all investment rate regression results shown in main Table 1 but holding the sample of firm-time observations fixed across specifications. The sample is restricted to firms that have both non-missing lagged realized and implied volatilities every fiscal year. Investment rate at fiscal year t is defined as I_t/K_{t-1} (capx/lagged net property plant & equipment from Compustat). Sample period is from 1963 to 2016. Specifications 1,2,4, and 5 are univariate, while 3 and 6 multivariate. Columns 1 and 4 are OLS while all others 2SLS. We address endogeneity concerns on firm-level volatility by instrumenting with industry-level (3SIC) non-directional exposure to 10 aggregate sources of uncertainty shocks. These include the lagged exposure to annual changes in expected volatility of energy, currencies, and 10-year treasuries (as proxied by at-the-money forward-looking implied volatilities of oil, 7 widely traded currencies, and TYVIX) and economic policy uncertainty from Baker, Bloom, and Davis (2016). Annual realized volatility is the 12-month standard deviation of daily stock returns from CRSP. Implied volatility is the annual average of daily (365-day-horizon) implied volatility of at-the-money-forward call options from OptionMetrics. Both firm and calendar-year fixed effects are included. Standard errors are clustered at the 3-digit SIC industry (in parentheses), with stronger results clustered at the firm level. To tease out the impact of 2nd moment uncertainty shocks from 1st moment aggregate shocks we also include as controls the lagged directional industry 3SIC exposure to changes in the price of each of the 10 aggregate instruments (i.e., 1st moment return shocks). These are labeled 1st moment 10IV$_{i,t-1}$. Firm-level Tobin's Q and stock return control for 1st moment effects at the firm-level. 2SLS first-stage F-statistics are Cragg-Donald (CD) for robust standard errors and Kleibergen-Paap (KP) for 3SIC clustered errors. The p-value for the Sargan-Hansen overidentification test for the validity of the instruments is also reported. Data availability on implied volatility of treasuries and oil restrict the start of the baseline 2SLS sample to fiscal year 2005. Results are robust to dropping these instruments from the set of 10 IVs and/or using their realized volatilies to expand the sample. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1, † p<0.15. See section 2 for data details.

Table D.15
Other real responses to volatility shocks for *ex-ante* financially constrained and unconstrained firms

Financial Constraint measure$_{i,t-5}$	(1)	(2)	(3)	(4)	(5)	(6)
	S&P Credit Ratings (1-6)					
	ΔIntang.	Invest$_{i,t}$	ΔCOGS$_{i,t}$		ΔSales$_{i,t}$	
$\Delta\sigma_{i,t-1}$	-0.036**	-0.005	-0.148***	-0.132***	-0.170***	-0.129**
	(0.018)	(0.023)	(0.035)	(0.039)	(0.064)	(0.058)
$\Delta\sigma_{i,t-1} \cdot Cred_Spread_t$	-0.058**	-0.047**	-0.233***	-0.213***	-0.199***	-0.176***
	(0.024)	(0.022)	(0.057)	(0.057)	(0.040)	(0.040)
$\Delta\sigma_{i,t-1} \cdot D_{i,t-5}^{Fin.Const}$		-0.052**		-0.022		-0.071**
		(0.023)		(0.029)		(0.034)
$\Delta\sigma_{i,t-1} \cdot D_{i,t-5}^{Fin.Const} \cdot Cred_Spread_t$		-0.007		-0.029†		-0.032†
		(0.018)		(0.020)		(0.020)
Observations	15,777	15,777	25,931	25,931	25,931	25,931
F-test 1st Stage Cragg-D	29.80	14.74	59.63	28.47	59.63	28.47
F-test 1st Stage Kleib.-P.	7.044	5.572	8.201	7.901	8.201	7.901
p-value Sargan-H J	0.080	0.115	0.031	0.050	0.034	0.024
p-value $(\beta_{\Delta\sigma}^{FC} + \beta_{CS\cdot\Delta\sigma}^{FC}) \geqslant 0$		0.005		0.039		0.004

Notes: Table reports 2SLS regression results of annual changes in intangible capital investment (R&D+selling, general and administrative expense from Compustat) (columns 1-2), changes in cost of goods sold (3-4), and changes in sales (5-6), where growth rates defined as $(x_t - x_{t-1})/(0.5 * x_t + 0.5 * x_{t-1})$. We examine the effect of 1-year lagged changes in firm-level annual realized volatility of daily CRSP returns, $\Delta\sigma_{i,t-1}$, and its interaction with the year t aggregate Moody's corporate credit spread BAA-AAA, $Credit_Spread_t$, and a dummy, $D_{i,t-5}^{Fin.Constrained}$, that takes value one for firms classified as ex-ante financially constrained using information in fiscal year $t-5$, zero otherwise. The credit spread is standardized to ease interpretation of coefficients. Estimates on $D_{i,t-5}^{Fin.Constrained} \cdot Credit_Spread_t$ and $D_{i,t-5}^{Fin.Constrained}$ in columns (2,4,6) are not presented in the Table to preserve space. A full set of firm-level controls, 1st moment aggregate return shock controls, and both firm and year fixed effects are included (e.g., as in baseline specification (3) in Table 2), thus $Credit_Spread_t$ is collinear with the time fixed effects. Regression models are in Eqs. [3] for columns (1,3,5), and [4] for (2,4,6) Standard errors in parenthesis are clustered at the 3digit SIC industry The credit spread is standardized to ease interpretation of coefficients. We address endogeneity concerns on firm-level volatility by instrumenting with industry-level (3SIC) non-directional exposure to 10 aggregate sources of uncertainty shocks, which include the lagged exposure to annual changes in expected volatility of energy, currencies, and 10-year treasuries (as proxied by option-implied volatilities of oil, 7 widely traded currencies, and TYVIX), and economic policy uncertainty from Baker, Bloom, and Davis (2016). Firms are either ex-ante financially constrained or unconstrained based on their constraint status in year $t-5$, as classified by: S&P credit ratings, which follows Duchin, Ozbas, and Sensoy (2010) and consider a firm constrained if it has positive debt and no bond rating and unconstrained otherwise (which includes firms with zero debt and no debt rating). We test the null $H_0 : (\beta_{\Delta\sigma}^{FC} + \beta_{CS\cdot\Delta\sigma}^{FC}) \geqslant 0$ that the *total negative effects* on real activity are at least as large for unconstrained firms, against the alternative $H_a : (\beta_{\Delta\sigma}^{FC} + \beta_{CS\cdot\Delta\sigma}^{FC}) < 0$ that the total negative effects of uncertainty shocks are larger for ex-ante constrained firms. Data sample is from fiscal year 2005 to December 2016. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1, † p<0.15.

Table D.16
Financial responses to volatility shocks for *ex-ante* financially constrained and unconstrained firms

Financial Constraint measure$_{i,t-5}$	(1)	(2)	(3)	(4)	(5)	(6)
	S&P Credit Ratings (1-6)					
	ΔTotal Debt$_{i,t}$		ΔPayout$_{i,t}$		ΔCash$_{i,t}$	
$\Delta\sigma_{i,t-1}$	-0.142**	-0.082	-0.271**	-0.242†	0.061	0.106
	(0.071)	(0.075)	(0.123)	(0.150)	(0.077)	(0.085)
$\Delta\sigma_{i,t-1} \cdot Cred_Spread_t$	-0.245***	-0.195**	-0.073	-0.035	0.173†	0.131†
	(0.076)	(0.079)	(0.162)	(0.157)	(0.112)	(0.090)
$\Delta\sigma_{i,t-1} \cdot D_{i,t-5}^{Fin.Const}$		-0.075		-0.023		-0.133*
		(0.078)		(0.134)		(0.072)
$\Delta\sigma_{i,t-1} \cdot D_{i,t-5}^{Fin.Const} \cdot Cred_Spread_t$		0.015		-0.107		0.076
		(0.053)		(0.092)		(0.072)
Observations	28,304	25,878	25,907	25,907	25,928	25,928
F-test 1st Stage Cragg-D	61.44	28.48	59.70	28.48	59.64	28.47
F-test 1st Stage Kleib.-P.	10.16	8.184	8.150	7.928	8.197	7.898
p-value Sargan-H J	0.893	0.796	0.209	0.282	0.199	0.449
p-value $(\beta_{\Delta\sigma}^{FC} + \beta_{CS\cdot\Delta\sigma}^{FC}) \geqslant 0$		0.207		0.151		0.224$^{\leq}$

Notes: Table reports 2SLS regression results of annual changes in total debt (columns 1-2), changes in corporate payout (cash dividend + share repurchase) (columns 3-4), and changes in cash holdings (cash and short-term investments) (columns 5-6), where growth rates defined as $(x_t - x_{t-1})/(0.5 * x_t + 0.5 * x_{t-1})$. We examine the effect of 1-year lagged changes in firm-level annual realized volatility of daily CRSP returns, $\Delta\sigma_{i,t-1}$, and its interaction with the year t aggregate Moody's corporate credit spread BAA-AAA, $Credit_Spread_t$, and a dummy, $D_{i,t-5}^{Fin.Constrained}$, that takes value one for firms classified as ex-ante financially constrained using information in fiscal year $t-5$, zero otherwise. The credit spread is standardized to ease interpretation of coefficients. Estimates on $D_{i,t-5}^{Fin.Constrained} \cdot Credit_Spread_t$ and $D_{i,t-5}^{Fin.Constrained}$ in columns (2,4,6) are not presented in the Table to preserve space. A full set of firm-level controls, 1st moment aggregate return shock controls, and both firm and year fixed effects are included (e.g., as in baseline specification (3) in Table 3), thus $Credit_Spread_t$ is collinear with the time fixed effects. Regression models are in eqs. [3] for columns (1,3,5), and [4] for (2,4,6) Standard errors in parenthesis are clustered at the 3digit SIC industry The credit spread is standardized to ease interpretation of coefficients. We address endogeneity concerns on firm-level volatility by instrumenting with industry-level (3SIC) non-directional exposure to 10 aggregate sources of uncertainty shocks, which include the lagged exposure to annual changes in expected volatility of energy, currencies, and 10-year treasuries (as proxied by option-implied volatilities of oil, 7 widely traded currencies, and TYVIX), and economic policy uncertainty from Baker, Bloom, and Davis (2016). Firms are either ex-ante financially constrained or unconstrained based on their constraint status in year $t-5$, as classified by: S&P credit ratings, which follows Duchin, Ozbas, and Sensoy (2010) and consider a firm constrained if it has positive debt and no bond rating and unconstrained otherwise (which includes firms with zero debt and no debt rating).We test the null $H_0 : (\beta_{\Delta\sigma}^{FC} + \beta_{CS\cdot\Delta\sigma}^{FC}) \geqslant 0$ that the *total negative effects* on financial activity are at least as large for unconstrained firms, against the alternative $H_a : (\beta_{\Delta\sigma}^{FC} + \beta_{CS\cdot\Delta\sigma}^{FC}) < 0$ that the total negative effects of uncertainty shocks are larger for ex-ante constrained firms. ($^{\leq}$): For cash (6) the null of this test is the opposite 1-sided test, so that we examine whether *total positive effects* are amplified. Data sample is from fiscal year 2005 to December 2016. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1, † p<0.15.