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THE FINANCE UNCERTAINTY MULTIPLIER

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ABSTRACT

We show how real and financial frictions amplify the impact of uncertainty shocks. We build a model with real frictions, and find adding financial frictions roughly doubles the impact of uncertainty shocks. Higher uncertainty alongside financial frictions induces the standard real-options effects on investment and hiring, but also leads firms to hoard cash, further reducing investment and hiring. We then test the model using a panel of US firms and a novel instrumentation strategy for uncertainty exploiting differential firm exposure to exchange rate and price volatility. These results highlight why in periods with greater financial frictions uncertainty can be particularly damaging.

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1 Introduction

This paper seeks to address two related questions. First, why are uncertainty shocks in some periods - like the 2007-2009 global financial crisis - associated with large drops in output, while in other periods - like the Brexit vote or 2016 US election - are accompanied by economic growth? Second, as Stock and Watson (2012) noted, uncertainty shocks and financial shocks are highly correlated. Are these the same shock, or are they distinct shocks with an interrelated impact, in which uncertainty is amplified by financial frictions?

To address these questions we build a heterogeneous firms dynamic model with two key extensions. First, real and financial frictions: on the real side investment incurs fixed cost,[1] and on the financing side issuing equity involves a fixed cost.[2] Second, uncertainty and financing costs are both stochastic, with large temporary shocks. The model is calibrated, solved and then simulated as a panel of heterogeneous firms.

We show two key results. Our first key result is a Finance Uncertainty Multiplier (hereafter FUM). Namely, adding financial frictions to the classical model of stochastic-volatility uncertainty 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 2.3%, but with *only* real frictions a drop of 1.2%. So, introducing financial costs roughly doubles the impact of uncertainty shocks on output.

Our second key result is 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 2.3% and 2.1% respectively, but jointly reduce output by 3.5%.

We summarize these two results below. This reports the peak drop in aggregate output in our calibrated model with only real frictions and an uncertainty shock is 1.2% (top left box).

[1]For example, Bertola and Caballero (1990), Davis and Haltiwanger (1992), Dixit and Pindyck (1994), Caballero, Engel, and Haltiwanger (1995), Abel and Eberly (1996), or Cooper and Haltiwanger (2006).

[2]See, for example, Hennessy and Whited (2005), Hennessy and Whited (2007), Bolton, Chen, and Wang (2013), Eisfeldt and Muir (2016), etc.

Adding financial frictions almost doubles the size of an uncertainty shock to 2.3% (bottom left box). Finally, adding a financial shock (as well as an uncertainty shock) increases the impact by another one half, yielding a drop in output of 3.5% (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 in simulation

	Uncertainty shock	Uncertainty + financial shocks
Real frictions	1.2%	n/a
Real+financial frictions	2.3%	3.5%

Notes: Results from simulations of 30,000 firms in the calibrated model (see section 3.4.1).

Alongside the negative impact of uncertainty and finance shocks on investment and employment, the model also predicts these shocks will lead firms to accumulate cash and reduce 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 panels also considers debt and shows that the total debt (the sum of the short-term and long-term debt) growth and the term structure of the debt growth (short-term debt growth to long-term debt growth ratio) are both negatively related with the VIX, implying firms cut debt (and particularly short-term debt) when uncertainty is high.

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. 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 our results on the negative impact of uncertainty-finance shocks on output are about 30% smaller but qualitatively similar.[3]

The second part of the paper tests this model using a micro-data panel of US firms with measures of uncertainty, investment, employment, cash, debt and equity payments. To address obvious concerns over endogeneity of uncertainty[4] we employ a novel instrumentation strategy for uncertainty exploiting differential firm exposure to exchange rate, factor price and policy uncertainty. This identification strategy works well delivering a strong first-stage F-statistics and passing Hansen over-identification tests. We find that higher uncertainty significantly reduces investment (in tangible and intangible capital) and hiring, while also leading firms to more cautiously manage their financial polices by increasing cash holdings and cutting dividends, debt, and stock-buy backs, consistent with the model (and macro data).

Our paper relates to three main literatures. First, the large uncertainty literature studying the impact of heightened uncertainty and volatility on investment and employment.[5] We build on this literature to show the joint importance of real and financial frictions for investment,

[3]One reason 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 (2016)).

[4]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.

[5]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). Several other papers 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)).

hiring and financial dynamics, and importantly how adding financial shocks can roughly double the impact of uncertainty shocks.

Second, the literature on financial frictions and business cycles.[6] 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 cannot be considered individually.

Finally, the finance literature that studies the determinants of corporate financing choices.[7] We are complementary to these studies by showing that uncertainty shocks have significant impact on firms' real and financial flows, examined in both calibrated macro models and well identified micro-data estimations.

The rest of the paper is laid out as follows. In section 2 we write down the model. In section 3 we present the main quantitative results of the model. In section 4 we describe the instrumentation strategy and international data that we use in the paper. In section 5 we present the empirical findings on the effects of uncertainty shocks on both real and financial activity of firms. Section 6 concludes.

2 Model

The model features a continuum of heterogeneous firms facing uncertainty shocks and financial frictions. 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.

[6]For example, Alessandri and Mumtaz (2016) and Lhuissier and Tripier (2016) show in VAR estimates a strong interaction effect of financial constraints on uncertainty. More generally, Gilchrist and Zakrajšek (2012), Jermann and Quadrini (2012), Christiano, Motto, and Rostagno (2014), and Gilchrist, Sim, and Zakrajsek (2014), Arellano, Bai, and Kehoe (2016), show that financial frictions are important to explain the aggregate fluctuations for the recent financial crisis. Caggiano et al (2017) show that uncertainty shocks have a bigger impact during recessions.

[7]For example, Rajan and Zingales (1995), Gomes (2001), Welch (2004), Moyen (2004), Hennessy and Whited (2005), Riddick and Whited (2009), DeAngelo, DeAngelo, and Whited (2011), Bolton, Chen, and Wang (2011), Rampini and Viswanathan (2013), Chen, Wang, and Zhou (2014), and Chen (2016) study the impact of various frictions on firms' financing policies, including equity, debt, liquidity management, etc.

2.1 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

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

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

$$Q_t = BP_t^{-\varepsilon}, \tag{2}$$

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

$$S(Z_t, K_t, L_t) = Z_t^{1-a-b} K_t^a L_t^b. \tag{3}$$

Wages are normalized to 1 denoted as $\bar{W}$. Given employment is flexible, we can obtain optimal labor.[8] 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

$$z_{t+1} = \rho_z z_t + \sigma_t \varepsilon_{t+1}^z \tag{4}$$

in which $z_{t+1} = \log(Z_{t+1})$, ε_{t+1}^z 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

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

chains

$$\sigma_t \in \{\sigma_L, \sigma_H\}, \text{where } \Pr(\sigma_{t+1} = \sigma_j | \sigma_t = \sigma_k) = \pi^{\sigma}_{k,j}. \tag{5}$$

Physical capital accumulation is given by

$$K_{t+1} = (1-\delta)K_t + I_t, \tag{6}$$

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:

$$G_t = c_k S_t \mathbf{1}_{\{I_t \neq 0\}}, \tag{7}$$

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.

We also assume that there is a fixed production cost $F \geq 0$. Firms need to pay this cost regardless of investment and hiring decisions every period. Hence firms' operating profit (Π_t) is revenue minus wages and fixed cost of production, given by

$$\Pi_t = S_t - \bar{W} L_t - F. \tag{8}$$

2.2 Cash holding

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

$$N_{t+1} = (1 + r_n) N_t + H_t, \tag{9}$$

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.

2.3 External financing costs

When the sum of investment in capital, investment adjustment cost and investment in cash exceeds the operating profit, firms can take external funds by issuing equity. External equity financing is costly for firms. 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.[9]

Because equity 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 cash accumulation, less investment adjustment costs

$$E_t = \Pi_t - I_t - H_t - G_t. \tag{10}$$

Furthermore, external equity financing costs vary over time and across firms.[10] 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 equity offerings (raising financing costs),

[9] 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%.

[10] Erel, Julio, Kim, and Weisbach (2012) show that firms' access to external finance markets also changes with macroeconomic conditions. 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.

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 SEO announcement is higher in contractions and lower in expansions, suggesting changes in information symmetries between firms and investors are likely to vary over time. Lee and Masulis (2009) show that seasoned equity issuance costs are higher for firms with poor accounting information quality.

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

$$\eta_t \in \{\eta_L, \eta_H\}, \text{where } \Pr\left(\eta_{t+1} = \eta_j | \eta_t = \eta_k\right) = \pi^{\eta}_{k,j}. \tag{11}$$

We do not explicitly model the sources of the equity financing costs. Rather, we attempt to capture the effect of the costs in a reduced-form fashion. The external equity costs Ψ_t are assumed to scale with firm size as measured by the revenue:

$$\Psi_t = \phi\left(\eta_t, \sigma_t\right) S_t \mathbf{1}_{\{E_t<0\}}. \tag{12}$$

Firms do not incur costs when paying dividends or repurchasing shares. So $\phi\left(\eta_t, \sigma_t\right)$ 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 equity financing cost depends on both time-varying financing condition η_t and time-varying uncertainty σ_t. This assumption captures the fact that periods of high external financing costs are associated with heightened uncertainty, consistent with Caldara, Fuentes-Albero, Gilchrist and Zakrajšek (2016) who document that change in VIX and change in CDS spread are positively correlated. As such, we assume $\phi\left(\eta_t, \sigma_t\right) = \eta_t + \lambda$ with $\lambda > 0$ when $\sigma_t = \sigma_H$, and $\phi\left(\eta_t, \sigma_t\right) = \eta_t$ when $\sigma_t = \sigma_L$, to capture the positive correlation between financing cost and uncertainty shock in the data.

2.4 Firm's problem

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

$$V_t = \max_{I_t, L_t, K_{t+1}, N_{t+1}} \left[E_t - \Psi_t + \beta \mathbb{E}_t V_{t+1} \right], \tag{13}$$

subject to firms' capital accumulation equation (Eq. 6) and cash accumulation equation (Eq. 9), where $E_t - \Psi_t$ captures the net payout distributed to shareholders.

3 Main results

This section presents the model solution and the main results. We first calibrate the model, 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.

3.1 Calibration

The model is solved at a quarterly frequency. Table 1 reports the parameter values used in the baseline calibration of the model. The model is calibrated using parameter values reported in previous studies, whenever possible, or by matching the selected moments in the data. To generate the model's implied moments, we simulate $3,000$ firms for $1,000$ quarterly periods. We drop the first 800 quarters to neutralize the impact of the initial condition. The remaining 200 quarters of simulated data are treated as those from the economy's stationary distribution.

Firm's technology and uncertainty 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%. 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, based on the average of the real annual S&P

index return in the data. This implies $\beta = 0.988$ quarterly. We set the return on cash holding $r_n = 0.8r_f$ to match the cash-to-asset ratio at 5% for the firms holding non-zero cash in the data. The fixed investment adjustment cost c_k is set to 1% and the fixed operating cost F is set to 20% of average revenue (set as the 20% of the median revenue on the revenue grid), consistent with the average SGA-to-sales ratio of 20% in the 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 (2016), 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 $\pi^{\sigma}_{H,H} = 0.94$.

Financing cost parameters. We set the baseline external equity financing cost parameter $\eta_L = 0.005$ and the high financing cost state $\eta_H = 10\eta_L = 0.05$.[11] 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.[12] In addition, we set $\lambda = 4\%$ so that the implied correlation between the external financing cost and the uncertainty is 69%, close to the correlation between Baa-Aaa spread and the VIX in the data in our sample. The calibrated financial costs are also average 1.78% of the sales (conditional on firms issuing equity), within the range the estimates in Altinkilic and Hansen (2000) and Hennessy and Whited (2005).

3.2 Policy functions

In this section, we analyze the policy functions implied by two different model specifications: 1) the model with real fixed investment costs only (real-only), and 2) the benchmark model with both real fixed investment costs and fixed financing costs (real and financial - the benchmark). Figures 2A and 2B plot the optimal investment policies associated with low and high uncertainty states of the real-only model (top left) and the benchmark model (top

[11] We have also solved the model with $\eta_H/\eta_L = \{2, 5, 8, 16, 20\}$ and find the quantitative results remain robust.

[12] We also solved 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 benchmark calibration.

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.[13] In the real-only 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 benchmark model, we see that the Ss band associated with high uncertainty state is bigger than the low uncertainty state, similar to the real-only model. However, optimal investment in the benchmark 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. When uncertainty is higher the real-option value of this financing constraint is larger, so the binding constraint region is bigger. This shows how real and financial constraints interact to expand the central region of inaction in Ss models.

Figure 2C plots the payout of the benchmark model (bottom left) of low and high uncertainty by fixing the idiosyncratic productivity and cash holding at their median grid points and financial shock at its low state. We see that firms both issue less equity and payout less in high uncertainty state.

3.3 Benchmark model result

In this subsection, we compare panel regression data from the model simulation with specifications, and also compare this to the real data. Specifically, we regress the rates of investment, employment growth, cash growth and payout-to-capital ratio (defined as positive payout scaled by capital) 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.

[13]Note that in the model with fixed investment costs only, optimal investment policies do not depend on cash holding since optimal cash holding is zero. Thus, figure 2A does not vary with different values of cash.

Table 2 starts in Row A by presenting the results from the real data (discussed in section 5) as a benchmark. As we see investment, employment and equity payouts significantly drop after an increase in uncertainty while cash holdings rises.[14] Row D below presents the benchmark simulation results (Real+financial frictions), and finds similar qualitative results with again drops in investment, employment and equity payouts and rising cash holdings[15]. In Row B we turn to the classic real frictions only model and see that the impact of uncertainty on investment and employment growth falls from -0.080 to -0.042 and -0.028 to -0.014 respectively. This implies a finance-uncertainty-multiplier of 1.90 (= 0.080/0.042) for investment and 2.0 (= 0.028/0.014) for employment. So introducing financial frictions to the classic uncertainty model roughly doubles the impact of uncertainty shocks.

In Row C we instead simulate a model with just financial frictions, and interestingly we still get a (smaller) negative impact of uncertainty on investment and employment, driven by firms desire to hoard cash when uncertainty increases, alongside a (larger) impact on increasing cash and cutting dividends. Hence, both the "real only" and "financial only" adjustment cost models have similar implications that uncertainty shocks reduce investment, employment and dividends and increase cash holdings. But, the real model has larger real (investment and employment) impacts and smaller dividend impacts and no cash impacts (without financial costs cash is zero). Finally, Row (E) models firms with no adjustment costs, resulting in very small positive Oi-Hartman-Abel impacts on investment and employment, no cash impacts, and larger dividend impacts due to more fluctuations in equity payouts.

3.4 Inspecting the mechanism

In this section, we inspect the model mechanism by first studying the impulse responses of the real and financial variables in the benchmark model and then compare them to the real-only model and the model with fixed financial costs only (financial-only). Furthermore, we also

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

[15]The real data results (Row A) and benchmark results (Row D) have similar quantitative magnitudes noting we did not calibrate our parameters to meet these moments.

run panel regressions in different model specifications to understand the marginal effect of real and financial frictions.

3.4.1 Impulse responses

To simulate the impulse response, 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 (noting that some events - like the 2007-2009 financial crisis - likely had more persistent initial impulses).

Uncertainty shocks Figure 3 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 1.2% and a gradual return to trend. This is driven by drops and recoveries in capital, labor and TFP. Capital and labor drop and recover due to increased 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 mis-allocation 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 mis-allocation. Dividend payout rises because firms with excess capital disinvest more with high uncertainty and hence payout more.

Turning to the benchmark model (red line, triangle symbols) with "real and financial adjustment costs" we see a much larger peak drop in output of 2.3%, alongside larger drops in capital and labor. This is driven by the interaction of financial costs with uncertainty which generates a desire by the firms to increase cash holdings (dividend payout falls but the drop is rather small) when uncertainty is high. Hence, we again see that adding financial costs to the classic model roughly doubles the impact of uncertainty shocks.

Finally, the model with only "financial adjustment costs" (blue line, circles) leads to a similar 1.0% peak drop in output. This is driven by a similar mix of a drop in capital as financial adjustment costs leads firms to hoard cash after an uncertainty shock, labor also drops (since this is complementary with capital), as does TFP due to less investment and hiring raising mis-allocation. The one notable difference in the impact of uncertainty shocks with real vs financial adjustment costs is the time profile on output, capital and 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. With financial costs the uncertainty shock only reduces investment by firms with limited internal financing, but this impact is more durable leading to a slower drop and recovery.

Financial shocks Figure 4 in contrast analyzes the impact of a pure financial shock - that is a shock to the cost of raising external finance, η, in equation (11) - for the simulation with real, financial and real+financial adjustment costs.

Starting first with real adjustment costs only (black line, x symbol) we see no impact because there are no financial adjustment costs in this model. Turning to the financial frictions but no real frictions model (blue line, circle symbols) we see only small impacts of financial shocks of 0.7% on output. The reason is with financial (but no real) frictions firms can easily save/dis-save in capital, so they are less reliant on external equity. Firms increase cash holdings and cut dividend payout due to increased financing costs. Finally, in the benchmark model (red line, triangle symbols) we see that, as before, the impact is roughly twice the size of the no financial costs model, with a drop in output of up to 2%, with similar falls in capital and labor. The reason is intuitive - if financial costs are temporarily increased firms will postpone raising external finance for investment, which reduces the capital stock and hence labor (by complementarity with capital). Moreover, cash holding and dividend payout displays sharper and more persistent rise and drop, respectively. TFP also shows a more modest drop due to the increase in mis-allocation (as investment falls), although this is smaller than for an uncertainty shock as firm-level TFP does not increase in volatility.

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. This plots the impact in the benchmark model of an uncertainty shock (black line, + symbols), a financial shock (blue line, circle symbols) and both shocks simultaneously (red line, triangle 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 (financial shocks cut capital and labor a bit more, uncertainty cuts aggregate TFP more; on financial flows, financial shocks increase cash holding and cut dividend payout much more than uncertainty shocks). But collectively their impact is significantly larger and more persistent - for example, the drop in output from an uncertainty or financial shock alone is 2.3% and 2.1% respectively, while jointly they lead to an output fall of 3.5%. 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 in a model will come closer to explaining the magnitude of this recession.

3.4.2 Robustness

In this section we consider - changes in parameter values and general equilibrium. These are plotted in Figure 6 and presented in Table A1.

Changes in parameter values We start by evaluating one-by-one changes a series of the parameter values listed in Table 2. The broad summary is that while the quantitative results vary somewhat across different parameter values, 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 these are roughly doubled by adding in financial adjustment costs.

In particular, we lower the high financing-cost-state-to-low-cost-state ratio (η_H/η_L) from

10 to 5 (while keeping the low financial cost state $\eta_L = 0.005$). This leads to a similar drop in output but with a faster recovery as it is now less expensive for constrained firms to finance investment (dark blue line with squares, Figure 6). Next, rather than set the transition probabilities of the financial shock to be the same as the uncertainty shock we set $\pi^{\eta}_{L,H} = 0.05$ and $\pi^{\eta}_{H,H} = 0.5$, which implies that financial shocks expected every 5 years and the average time of the economy in high financing cost state is 10% (similar to the calibration of the credit shocks in Khan and Thomas (2013)). As we see (black line, circles) this leads to a very similar drop but faster recovery from the uncertainty-finance shock because the finance shocks is now less persistent.

We also try reducing the fixed production cost (F) to 10% of the sales rather than 20% in the baseline calibration. We see (blue-dash line, crosses) this produces almost identical drop and 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. Furthermore, we increase the investment adjustment cost (c_k) to 2% of the sales instead of 1% in the baseline and we see this change also leads to a similar drop of output to the baseline but somewhat faster recovery (yellow line, stars). 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 bigger peak drop in output to around 4.2% (3.5% 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 (2016), 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 10% 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 slightly smaller drop but somewhat faster rebound (pink-dash line with pluses in Figure 6).

4 Data and instruments

We first describe the data and variable construction, then the identification strategy.

4.1 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 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 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 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 uncertainty from CRSP stock returns and *option-implied* uncertainty from OptionMetrics. Realized uncertainty 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).[16] 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 (B).

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 (implicitly the change in gross capital stock) 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 and ratios of real and financial variables are then winsorized 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 lagged level of Tobin's Q we follow Leary and Roberts (2014) and include controls for lagged levels of firm tangibility, book leverage, return on assets, log sales, and stock returns. The Appendix (B) details the construction of these variables.

4.2 Identification strategy

Our identification strategy exploits firms' differential exposure to aggregate uncertainty shocks in energy, currency, policy, and treasuries to generate exogenous changes in firm-level

[16] 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).

uncertainty. The idea is that some firms are very sensitive to, for example, oil prices (e.g. energy intensive manufacturing and mining firms) while others are not (e.g. retailers and business service firms), so that when oil-price volatility rises it shifts up firm-level volatility in the former group relative to the latter group. Likewise, some industries have different trading intensity with Europe versus Mexico (e.g. industrial machinery versus agricultural produce firms), so changes in bilateral exchange rate volatility generates differential moves in firm-level uncertainty. Finally, some industries - like defense, health care and construction - are more reliant on the Government, so when aggregate policy uncertainty rises (for example, because of elections or government shutdowns) firms in these industries experience greater increases in uncertainty.

Our estimation approach is conceptually similar to the classic Bartik identification strategy which exploits different regions exposure to different industry level shocks, and builds on the paper by Stein and Stone (2013).

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 and currencies, return on treasury bonds, and changes in daily policy uncertainty. That is, for firms i in industry j , $sensitivity_i^c = \beta_j^c$ is estimated as follows

$$r_{i,t}^{risk\_adj} = \alpha_j + \sum_c \beta_j^c \cdot r_t^c + \epsilon_{i,t} \tag{14}$$

where $r_{i,t}^{risk\_adj}$ is the daily risk-adjusted return on firm i (explained below), 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 3-digit Standard Industrial Classification (SIC) codes. 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, and thus increases the precision of the estimates. Moreover, we allow these industry-level sensitivities to be time-varying by estimating them using 10-year rolling windows of past daily data. Further, as explained below, we exploit these time-varying factor exposures to construct pre-estimated sensitivities and instruments that are free of look-ahead bias concerns in our main regressions, which run second-stage 2SLS specifications of real and financial outcomes on past uncertainty shocks.

The risk-adjusted returns in (14) are the residuals from running firm-level time-series regressions of daily CRSP stock returns on the Carhart (1997) four-factor asset pricing model. In particular, using the same 10-year rolling window used in (14) we define firm daily risk-adjusted returns as the residuals of regressing firms' excess return on the daily Carhart factors:

$$r_{i,t}^{excess} = \alpha_i + \beta_{i,mkt} \cdot MKT_t + \beta_{i,HML} \cdot HML_t + \beta_{i,SMB} \cdot SMB_t + \beta_{i,UMD} \cdot UMD_t + \varepsilon_{i,t} \quad (15)$$

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 factor data are obtained from CRSP.

We adjust returns for risk to address concerns over whether the sensitivities to energy, currencies, treasuries, and policy - β_j^c in equation (14)- are capturing systematic "risks" rather than exposure to the prices of interest. Our main results are fairly similar when we use longer or shorter rolling windows, of 15 and 5 years, in both (14) and (15) and raw or risk adjusted returns.

The daily independent variables in (14) 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 [17], the return on the US 10-year treasury note [18], and the growth in economic policy uncertainty from Baker, Bloom, and Davis (2016). For these 10 aggregate market price shocks (oil, 7 currencies, treasuries, and policy) we need not

[17] 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 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.

[18] 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.

only their daily returns (for calculating the sensitivities β_j^c in equation (14)) but also their implied volatilities σ_t^c as measures of aggregate sources of uncertainty.

Construction of instruments To instrument for firm-level uncertainty shocks, $\Delta\sigma_{i,t}$, we also require data on aggregate uncertainty shocks, $\Delta\sigma_t^c$. We define the annual uncertainty on oil, currency, and 10-year treasuries as the 252-day average of daily implied volatility of oil and currencies from Bloomberg and for treasuries we use the 252-day average of daily implied volatility for the 10-year US Treasury Note from the Cboe/CBOT (ticker TYVIX). Likewise, for annual policy uncertainty we employ the 365-day average of the US economic policy uncertainty index from Baker, Bloom, and Davis (2016). These 10 annual aggregate uncertainty measures, σ_t^c, are used in constructing cross-industry exposures to aggregate uncertainty shocks, $\mid \beta_j^{c,weighted} \mid \cdot\Delta\sigma_t^c$.

We do this in two steps. First, we adjust the factor sensitivities estimated in (14) for their statistical significance. In particular, within each industry we construct significance-weighted sensitivities $\beta_j^{c,weighted} = \omega_j^c \cdot \beta_j^c$, where the first term is a sensitivity weight constructed from 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, $\omega_j^c = \frac{abs(t_j^c)}{\sum^{c} abs(t_j^c)}$. Thus, we adjust the sensitivities within each industry by their statistical power in (14). However, in constructing the weights ω_j^c we first set to zero each individual t-statistic for which the corresponding sensitivity is statistically insignificant at the 10% level. This is done both before taking the absolute value of each t-statistic and the sum of their absolute values. Thus, the significance-weighted sensitivities $\beta_j^{c,weighted}$ can be zero for certain industries. However, recalling that the raw sensitivities β_j^c in (14) are estimated in rolling windows, the significance-weighted sensitivities $\beta_j^{c,weighted}$ need not be zero at every moment in time. Indeed, our sample shows that 3-SIC industries fluctuate both in their extensive and intensive exposure to the each of our 10 instruments over time. Our weighting scheme captures and exploits both margins.

Second, we construct 10 composite terms $\mid \beta_j^{c,weighted} \mid \cdot\Delta\sigma_t^c$, which we refer to as the industry-by-year exposure for uncertainty shocks, where the first term is the absolute value of the significance-weighted sensitivity explained above and $\Delta\sigma_t^c$ is the annual growth in the aggregate implied volatility of the instrument. Thus, our instrumental variables estimation uses 10 instruments, the oil exposure term, the seven currencies exposure terms, the 10-year treasury exposure term, and the policy-uncertainty exposure term. These 10 composite industry-by-year exposure for uncertainty shocks are the instruments used in our 2SLS regressions that instrument for firm-level uncertainty shocks.

Finally, to disentangle second moment effects from first moment effects of our 10 instruments, we also include as controls in the second stage of the 2SLS regressions the exposure to the returns of each instrument (i.e., first moment controls). That is, in the regressions we also include 10 first moment composite terms $\beta_j^{c,weighted} \cdot r_t^c$.[19] Thus, our empirical examination focuses on the effects of uncertainty shocks above and beyond first moment effects. At the firm-level, our main set of controls further includes each individual firms' measure of first moment effects, i.e., the CRSP stock return of the firm, $r_{i,t}$ (which accounts for discount rate channel effects).

5 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.

5.1 Investment results

Table 3 examines how uncertainty influences future capital investment rates. Column 1 presents the univariate Ordinary Least Squares regression results of investment rate on lagged annual *realized* stock return volatility shocks. We observe highly statistically significant coefficients (t-stat of 20.075) on return volatility, showing that firms tend to invest more when

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

their firm-specific uncertainty is low. Column 4 presents the corresponding OLS univariate regression results of investment rate on lagged firm-level *implied* volatility shocks (from OptionMetrics). The sign of the coefficient is consistent with realized volatility shocks, but the size is more than twice as large, potentially because implied volatility is a better measure of uncertainty.[20]

One obvious concern with these OLS regressions is endogeneity - for example, changes in firms' investment plans could change stock-prices. Using lagged uncertainty mitigates some of these concerns, but given stock prices are forward looking movements in returns still suffer from endogeneity concerns. Therefore. we try to address endogeneity concerns with our instrumentation strategy. In particular, columns 2 and 3 instrument lagged *realized* volatility shocks using the full set of 10 instruments 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. In all cases we find that uncertainty shocks lead to significant drops in firm-level investment.

The point estimates of the coefficients on instrumented uncertainty shocks with the full set of controls are roughly of comparable magnitude to the univariate OLS point estimates (e.g., columns 3 and 1). Our full set of lagged controls includes Tobin's Q, log sales and stock-returns to control for firm moment shocks, as well as book leverage, profitability (return on assets) and tangibility to control for financial conditions. Our multivariate specifications also include firm and time fixed effects and cluster standard errors at the 3-SIC industry (which is the same level at which our instrumentation strategy estimates factor exposures). In all instrumented cases, rises in uncertainty is a strong predictor of future reductions in capital investment rates.

In terms of magnitudes the results imply that a two-standard deviation increase in realized volatility (see the descriptive statistics in Table A2) would reduce investment by between 4% to 6% (using the results from our preferred multivariate specifications in column (3) and (6)).

[20]We reestimate both specifications in columns (1) and (4) on a common sample of 17,391 observations in table (A5) and find the realized and implied volatility coefficients are -0.033 and -0.079.

This is moderate in comparison to firm-level investment fluctuations which have a standard deviation of 24.7%, but is large when considering that annual investment rates drop between 2% to 6% during recessions as show in Figure 1.

5.1.1 First stage results

The first stage instrumental investment results are shown in Table 4. Columns (1) and (2) report the first stages for the univariate IV columns (2) and (4) from table 3. We see that the F-statistics indicate a well identified first stage with respective values of 157.6 and 78.37 for the Cragg-Donald (CD) F-Statistics (robust standard-errors), and 18.58 and 14.96 for the Kleibergen-Paap (KP) F statistic (SIC-3 digit clustering). We also find the Hansen over-identifying test does not reject the validity of our instruments with p-values of 0.349 and 0.625. As another check of our identification strategy we would like to see that each of our instruments is individually positively, and generally significantly correlated with uncertainty shocks. Indeed, we see in columns (1) and (2) that all 10 instruments are positive and mostly significant in the first stage.

We repeat the above examination but adding our full set of controls, where columns (3) and (4) in Table 4 present the first stage for the multivariate IV regressions of columns (3) and (6) from table 3. Even when we add our full set of controls we see a well satisfied relevance condition, with CD F-statistics of 171.1 and 58.59, and KP F-statistics of 17.57 and 11.14, respectively, and non-rejected Sargan-Hansen validity test p-values of 0.955 and 0.950. Moreover, each instrument remains individually positively correlated with uncertainty shocks.

5.2 Intangible capital, employment, and cost of goods sold

Table 5 examines the predictive and causal 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 and R&D, which extends the approach of Eisfeldt and Papanikolaou (2013)), Panel B examines employment, and Panel C examines the cost of goods sold. In each panel we present the same 6 specification results presented for investment in Table 3. but to preserve space we drop the point coefficient estimates on controls and keep only the estimates on lagged uncertainty shocks.

The three panels show that realized and implied volatility shocks are negatively related to future changes in intangible capital investment, employment, and cost of goods sold. As with investment, these regressions show a strong first-stage with 3-SIC clustering KP F-statistics in the range of 9.62 to 17.46 in all multivariate specifications that include a full set of controls, columns (3) and (6). In our preferred specification of column (3), which instruments realized lagged uncertainty shocks, both intangible capital investment and cost of good sold drop upon higher realized uncertainty (significant at the 5 and 1 percent, respectively), while the response of employment is negative but not statistically significant.

Overall, the three panels confirm the robustness of the causal impact of uncertainty shocks on real firm activity, even in the presence of extensive first-moment and financial condition controls, plus an extensive instrumentation strategy for uncertainty shocks.

5.3 Financial variables

Table 6 examines how firm uncertainty shocks affect future changes in financial variables. In particular, Panel A examines total debt, Panel B dividend payout, and Panel C cash holdings. Panel A indicates that increases in uncertainty reduce the willingness of firm's to increases their overall debt. The correlations are strong and significant in both the OLS and instrumental variable regressions. Panel B indicates that firm's take a more cautious financial approach toward corporate payout. Consistent with a precautionary savings motive, rises in firm uncertainty causes a large reduction in cash dividend payout. Similarly, Panel C further evidences a precautionary savings channel as cash holdings increase upon large uncertainty shocks. In particular, firms accumulate cash reserves and short-term liquid instruments following uncertainty rises.

For the preferred specifications in columns (3) and (6) all three panel show highly significant point estimates (at the 5% and 1%), strong first stage F-statistics (all KP F-statistics above 11.1), and non-rejections on the Sargan-Hansen over-identifying test. This highlights that our instrumental strategy based on exchange rate and factor price volatility works well not only for real outcomes but also for financial.

5.4 Instrument and credit supply robustness

In Appendix Table A3 we investigate the main multivariate investment results dropping each instrument one-by-one in columns (2) to (9) to show our results are not being driven by any particular instrument (noting in column (10) we drop the oil and treasury instruments together to allow us to extend our sample size to 42,388)[21]. As we see across the columns the first stage results for investment are impressively robust - the tougher KP F-test test is in the range of 12.09 to 19.84 in all specifications (the CD F–test is always above 99), and the Hansen over-identifying test does not reject in any specification with p-values of 0.9 or above. Moreover, all real and financial variables examined in baseline column (1) are robust. Taken together, the results across all columns indicate that our identification results are not driven by one particular instrument, but instead are driven by the combined identification of energy, exchange rate, policy, and treasury uncertainty driving firm-level uncertainty fluctuations and firm decisions. This suggests that our identification strategy will likely be broadly useful for a wide-range of models of the causal impact of uncertainty on firm behavior.

In Appendix Table A4 we investigate the robustness of the results to both adjusting volatility shocks by firm leverage and including controls for financial constraints. In columns (1) and (1A) we regress all main real and financial outcomes on lagged leverage-adjusted realized and implied volatility shocks, respectively. Here we adjust uncertainty effects by multiplying either volatility by firm's book leverage, i.e., $\sigma_{i,t} \cdot \frac{E_{i,t}}{E_{i,t}+D_{i,t}}$ where E is book equity (CEQ in Compustat) and D is total debt. The results are robust to these levered-volatility measures. Moreover, one concern could be that uncertainty reduces financial supply - for

[21] 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.

example, banks are unwilling to lend in periods of high uncertainty - which causes the results we observe. To try to address this we include a variety of different controls for firms financial conditions and show our baseline results are robust to this. In particular for both the realized and implied volatility specifications we include controls for firm: CAPM-beta (defined as the covariance of the firms daily returns with the market returns in the past year, scaled by the variance of the market) in columns 2 and 2A, a broad set of firm financial constraint controls in columns 3 and 3A - which include the lags for the Whited and Wu (2006) index, size and age (SA) index of Hadlock and Pierce (2010), the Kaplan and Zingales (1997) index, reciprocal of total assets, reciprocal of employees, and reciprocal of age -where age is the number of years since firm incorporation-, the firms long-term credit rating from S&P in columns 4 and 4A (which consist of a full set of dummies based on every possible credit rating category given to firms by S&P on long-term debt, where the omitted dummy is for no credit ratings), and all of the previous measures combined in columns 5 and 5A. In summary, as we can see from Table A4 including these financial supply variables does not notably change our results. So while these are not perfect controls for financial conditions, the robustness of our results to their inclusion helps address concerns that financial supply conditions are the main driver of our results.

In Appendix Table A5 we re-examine our main investment Table 3 but holding the sample of firm-time observations to be the same across 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 17,391 observations across all columns. Compared to the main Table 3 the point estimates on the coefficients are largely comparable in both magnitude and statistical significance. Therefore, differences in point estimates across specifications (2SLS vs OLS, univariate vs multivariate, and realized vs implied volatility shocks) are primarily due to the underlying specifications themselves and not due to differences in sample size.

Finally, in Appendix Table A6 we further present dividend payout results when defined as a ratio of lagged total assets ($\frac{Payout_{i,t}}{AT_{i,t-1}}$). The causal effects of uncertainty shocks are robust to using this alternative definition of dividend payout, which complements the dividend growth results presented in Panel B of Table 6.

5.5 The finance uncertainty multiplier

Finally, Table 7 shows the results from running a series of finance-uncertainty interactions on the data during the core Jan. 2008-Dec. 2009 period of the financial crisis. By running double and triple interaction of uncertainty with financing frictions we attempt to tease out the finance-uncertainty multiplier effects examined in the model of section 2. In particular, Table 7 examines the impact of realized volatility shocks on investment for financially constrained and unconstrained firms during financial crisis and non-crisis years. We do this by running the following specification and subsets of it:

$$I_{i,t}/K_{i,t-1} = \beta_0 + \beta_1 \Delta\sigma_{i,t-1} + \beta_2 D_{crisis\_year,t}$$
$$+\beta_3 D_{crisis\_year,t} \cdot \Delta\sigma_{i,t-1} + \beta_4 D_{fin.constrained,i,t-1} + \beta_5 D_{fin.constrained,i,t-1} \cdot \Delta\sigma_{i,t-1}$$
$$+\beta_6 D_{crisis\_year,t} \cdot D_{fin.constrained,i,t-1} + \beta_7 D_{crisis\_year,t} \cdot D_{fin.constrained,i,t-1} \cdot \Delta\sigma_{i,t-1} \qquad (16)$$

where $\Delta\sigma_{i,t-1}$is firm $i's$ growth of realized annual vol from year $t-2$ to $t-1$, $D_{crisis\_year,t}$ is a dummy that takes value of 1 for all firm fiscal-year observations of investment rate ending in calendar years 2008 and 2009, i.e., core years of the financial crisis which comprise the core months of the great recession in which firms would have observed at least 6 months of heightened financial frictions in their annual accounting reports, zero otherwise, and $D_{fin.constrained,i,t-1}$is a dummy that takes value of 1 for firms classified as financially constrained (e.g., according to Whited-Wu index) in year $t-1$, zero otherwise. The coefficient β_7 indicates whether the effect of uncertainty on investment is different for financially constrained firms during crisis years relative to unconstrained firms.[22]

[22] There is a large literature on measuring firm-level financial constraints. Any proxies are usually subject to critiques on whether they truly capture constraints or just noise. We employ a total of 6 different proxies to take rough cuts to our Compustat data. We thank Toni Whited for suggestions on this front, e.g., adding the SA index.

Column (1) presents our baseline 2SLS multivariate specification with full set of controls presented in Table 3 column (3). Column (2) interacts past uncertainty shocks with the contemporaneous crisis dummy, $D_{crisis\_year,t}$. The regression indicates that the effects of uncertainty shocks on investment are much larger in the period of high financing frictions in the core crisis years of the great recession, as seen in the highly significant interaction term $D_{crisis\_year,t} \cdot \Delta\sigma_{i,t-1}$. This is consistent with the main thesis in this paper that financial constraints substantially amplify the impact of uncertainty shocks.

To disentangle and further understand these financing frictions vs uncertainty effects, columns (3) to (8) run the full difference-in-difference-in-difference specification in 16 , where we employ a total of 6 proxies for financing frictions to classify firms into financially constrained and unconstrained groups. For example, in column (4) using each firm's financial constraint Whited-Wu index at every fiscal year $t-1$ we classify firms into constrained and unconstrained groups using the 40 and 60 percentile cutoffs obtained from the cross-sectional fiscal-year distribution of the given index. We consider a firm constrained if its $t-1$ index value is equal to or greater than the 60 percentile and unconstrained if equal to or less than the 40 percentile. We exclude firm-time observations in the middle 50+/-10 percentiles to increase precision in the classification of firms.[23] We do this in all but the S&P credit-rating financial constraint measure, column (3). 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]

In sum the 6 measures of financial constraints are constructed using S&P ratings column (3), Whited-Wu index column (4), reciprocal of employees column (5), reciprocal of total assets column (6), reciprocal of age column (7) in which age is defined as the number of years since firm incorporation, and the SA index based on size and age of Hadlock and Pierce

[23]Our inferences are similar if we expand or reduce the window of observations dropped in the middle: 50+/-15 and/or 50+/-5 percentiles, i.e., comparing top vs bottom 30% and/or 45% of firms. Moreover, results are similar if we classify firms as ex-ante financially constrained or unconstrained using two-year past indexes of financial constraints.

[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).

(2010) column (8). In all specifications we include both firm and calendar-year fixed effects, and cluster standard errors at the 3 digit SIC industry. All specifications include full set of controls of baseline specification column (1).

Using the Whited-Wu index column (4) to classify firms, the results indicate that investment rates drop upon larger uncertainty shocks (negative and significant β_1 coefficient on uncertainty shock $\Delta\sigma_{i,t-1}$, at the 5%), the drop is more pronounced during the core crisis years of 2008 and 2009 (negative and significant β_3 coefficient on the double interaction term $D_{crisis\_year,t} \cdot \Delta\sigma_{i,t-1}$, at the 1%), and the negative real effect on investment is amplified for ex-ante financially constrained firms during the core crisis years (as determined by the negative and significant β_7 coefficient on the triple interaction term $D_{crisis\_year,t} \cdot D_{fin.constrained,i,t-1} \cdot \Delta\sigma_{i,t-1}$, at the 5%).

Using other measures of financial constraints in columns (3) to (8) give similar inferences: uncertainty matters (causally), it matters even more during periods of financial constraints, and it matters most for the most ex-ante constrained firms. Hence, overall Table 7 provides important empirical evidence in support of the testable predictions of the model of section 2 for an interactive effect of financial constraints and uncertainty in deterring firm investment activities during the 2008-2009 period of the financial crisis.

To show this graphically in the raw data Figure 7 plots investment rates for financially constrained and unconstrained firms from 2003 to 2013. We normalize the investment rates of both groups of firms to their respective values of investment rates in 2006. Financial constraints are defined as a firm having short or long-term debt but no public bond rating (see, e.g., Faulkender and Petersen (2006) and Duchin, Ozbas, and Sensoy (2010)). Volatility is the annual realized stock return volatility of all firms in the sample. It is clear that constrained and unconstrained firms' investment rates track each other closely until the Great Recession, at which point the constrained firms' investment drop substantially more than unconstrained firms. As uncertainty recedes post 2012 the gaps start to recede again as the investment rates begin to converge. There are of course many ways to explain this difference (e.g. small vs large firms), but it is at least consistent with the model of uncertainty shocks mattering more for more financially constrained firms.

As a robustness Appendix Table A7 repeats the examination done in Table 7, but using option-implied firm-level uncertainty shocks instead of realized uncertainty shocks. The inferences on the economic and financial importance of uncertainty shocks are robust to these forward-looking uncertainty data.

6 Conclusion

This paper studies the impact of uncertainty shocks on firms' real and financial activity both theoretically and empirically. We build a dynamic model which adds two key components: first, real and financial frictions, and second, uncertainty and financial shocks. This delivers three key insights. First, combining real and financial frictions roughly doubles the impact of uncertainty shocks - this is the finance uncertainty multiplier. Second, 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. Finally, 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 impact of uncertainty shocks on real and financial variables matches the evidence from the recent financial crisis.

We then use empirical data on U.S. listed firms to test the model using a novel instrumentation strategy. Consistent with the testable implications, uncertainty shocks reduce firm investment (tangible and intangible) and employment on the real side, and increase cash holdings, while reducing payouts and debt on the financial side.

In all, our theoretical and empirical analyses show that real and financial frictions are quantitatively crucial to explain the full impact of uncertainty shocks on real and financial activity.

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Table 1

Parameter values under benchmark 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	80% of the risk-free rate (the cash to asset ratio for cash holding firms)
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 cost of investment	c_k	0.01	1% of quarterly revenue (Also tried 2% & 4%)
Fixed operating cost	F	0.2	Firms' average SG&A to sales ratio
Uncertainty shock (2 state Markov)			
Conditional volatility of productivity	σ_L	0.051	Baseline uncertainty (Bloom et al 2016)
Conditional volatility in high uncertainty state	σ_H	0.209	Uncertainty shocks 4.1*baseline uncertainty (Bloom et al 2016)
Transition probability low to high uncertainty	$\pi^{\sigma}_{L,H}$	2.60%	Uncertainty shocks expected every 9.6 years (Bloom et al 2016)
Transition probability remaining in high uncertainty	$\pi^{\sigma}_{H,H}$	94%	Quarterly probability of remaining in high uncertainty (Bloom et al 2016)
Persistence of logged idiosyncratic productivity	ρ_z	0.95	Quarterly persistence of idiosyncratic productivity (Khan & Thomas 2008)
Stochastic financing cost (2 state Markov)			
Low external financing cost state	η_L	0.005	Low cost .5% of output (Altinkilic and Hansen 2000)
High external financing cost state	η_H	0.05	High cost 5% of output (Altinkilic & Hansen 2000). Robust 2.5%,10%
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%	Same as uncertainty shock (Also tried 50%)
Impact of uncertainty on financial cost	λ	0.04	Correlation between the Baa-Aaa spread and VIX

This table presents the predetermined and the calibrated parameter values of the benchmark model.

Table 2
Coefficient on changes in volatility for real and financial variables

	Real		Financial	
	I/K	ΔEmp	ΔCash	Div/K
A: Data				
ΔVolatility	-0.089	-0.074	0.227	-0.019
B: Real frictions				
ΔVolatility	-0.042	-0.014	na	-0.007
C: Financial frictions				
ΔVolatility	-0.021	-0.004	1.032	-0.036
D: Real+financial frictions				
ΔVolatility	-0.080	-0.028	0.487	-0.012
E: No frictions				
ΔVolatility	0.003	0.006	na	-0.021

Row (A) Data reports the results for investment rate, employment growth, cash growth, and equity payout to assets ratio from columns (2) of tables (3), (5), (6), (A6) respectively. Rows (B) to (E) reports the model counterparts from regressions using simulation data on volatility ($\sigma_{i,t}$) growth. The reported statistics in the model are from simulated data with 3000 firms and 200 quarterly observations. I/K is the investment rate, ΔEmp is the employment growth, ΔCash is the cash growth rate, and Div/K the dividend scaled by capital in the model and cash dividend plus repurchase scaled by total assets 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).

Table 3
Investment rate

	(1)	(2)	(3)	(4)	(5)	(6)
Investment rate$_{i,t}$	OLS	IV	IV	OLS	IV	IV
	Realized	Realized	Realized	Implied	Implied	Implied
ΔVolatility$_{i,t-1}$	-0.032***	-0.089***	-0.030***	-0.090***	-0.225***	-0.078**
	(-20.075)	(-3.923)	(-2.948)	(-10.449)	(-4.235)	(-2.454)
Book Leverage$_{i,t-1}$			-0.050***			-0.037***
			(-8.173)			(-5.583)
Stock Return$_{i,t-1}$			0.008***			0.005*
			(2.953)			(1.808)
Log Sales$_{i,t-1}$			-0.023***			-0.022***
			(-7.330)			(-5.290)
Return on Assets$_{i,t-1}$			0.142***			0.132***
			(5.558)			(3.910)
Tangibility$_{i,t-1}$			-0.115***			-0.123***
			(-5.801)			(-3.355)
Tobin's Q$_{i,t-1}$			0.049***			0.054***
			(9.892)			(8.341)
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	124,206	28,419	28,132	26,030	17,572	17,391
F 1st st. Cragg-D		157.6	171.1		78.37	58.59
F 1st st. Kleib.-P		18.58	17.57		14.96	11.14
p-val Sargan–H J		0.349	0.955		0.625	0.950

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. Only 1 and 4 are OLS while all others 2SLS. The latter instrument lagged changes in firm-level volatility with industry-level (3SIC) exposure to 10 aggregate lagged 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) implied volatility of at-the-money-forward call options from OptionMetrics. Regressors lagged by 1-year. Both firm and calendar-year fixed effects are included. Standard errors are clustered at the 3-digit SIC industry. To tease out the impact of 2nd moment uncertainty shocks we also include as controls the lagged exposure to changes in the return on each of the 10 aggregate instruments (i.e., 1st moment shocks). Data availability on implied volatility of treasuries and oil restrict the start of the 2SLS sample to fiscal year 2006. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1, † p<0.15. t-statistics are in parentheses. See section 4 for data details.

Table 4
Investment rate - 2SLS 1st stage results

Specification:	Univariate		Multivariate	
Set-up: ΔVolatility$_{i,t-1}$	Realized	Implied	Realized	Implied
ΔVol Exposure Cad$_{i,t-1}$	3.643***	1.442***	3.353***	1.234***
	(4.64)	(3.66)	(4.54)	(3.35)
ΔVol Exposure Euro$_{i,t-1}$	1.338***	0.643***	1.211***	0.479***
	(4.34)	(3.57)	(4.13)	(2.80)
ΔVol Exposure Jpy$_{i,t-1}$	2.117***	0.244	2.096***	0.298
	(3.53)	(0.55)	(3.55)	(0.68)
ΔVol Exposure Aud$_{i,t-1}$	5.142***	1.769***	5.395***	1.763***
	(7.44)	(5.64)	(8.90)	(5.72)
ΔVol Exposure Sek$_{i,t-1}$	4.236***	1.277***	4.914***	1.575***
	(7.56)	(3.57)	(7.73)	(4.10)
ΔVol Exposure Chf$_{i,t-1}$	2.046***	1.300***	2.319***	1.360***
	(5.75)	(6.10)	(5.90)	(5.44)
ΔVol Exposure Gbp$_{i,t-1}$	2.971***	1.841***	2.697***	1.655***
	(5.05)	(4.24)	(5.05)	(4.51)
ΔVol Exposure Policy$_{i,t-1}$	588.990***	239.159*	616.792***	195.837*
	(3.02)	(1.94)	(3.32)	(1.72)
ΔVol Expos.Treasury$_{i,t-1}$‡	3.116***	1.100***	2.969***	0.811***
	(8.43)	(4.45)	(8.31)	(4.10)
ΔVol Exposure Oil$_{i,t-1}$	3.132***	1.938***	4.549***	1.796***
	(9.79)	(10.33)	(5.90)	(6.06)
Observations	28,419	17,572	28,132	17,391
F-test 1st stage Cragg-Donald	157.6	78.37	171.1	58.59
F-test 1st stage Kleibergen-Paap	18.58	14.96	17.57	11.14
p-value Hansen-Sargan J	0.349	0.625	0.955	0.950

Table presents the 2SLS first stage regression results of 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 (2) and (5) in Table 3, while columns 3 and 4 are the multivariate first stage results of specifications (3) and (6). We instrument lagged changes in firm-level volatility with industry-level (3SIC) exposure to 10 aggregate lagged 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) implied volatility of at-the-money-forward call options from OptionMetrics. Regressors lagged by 1-year. Both firm and calendar-year fixed effects are included. Standard errors are clustered at the 3-digit SIC industry. To tease out the impact of 2nd moment uncertainty shocks we also include as controls the lagged exposure to changes in the return on each of the 10 aggregate instruments (i.e., 1st moment shocks). Data availability on implied volatility of treasuries and oil restrict the start of the 2SLS sample to fiscal year 2006. ‡ :The coefficients on treasuries are scaled upward by a factor of 1000 for presentational purposes. Statistical significance: *** $p<0.01$, ** $p<0.05$, * $p<0.1$, † $p<0.15$. t-statistics are in parentheses. See section 4 for data details.

Table 5
Additional real quantities

	(1) OLS Realized	(2) IV Realized	(3) IV Realized	(4) OLS Implied	(5) IV Implied	(6) IV Implied
A: ΔIntangible Capital Investment$_{i,t}$						
ΔVolatility$_{i,t-1}$	-0.054***	-0.097***	-0.036**	-0.137***	-0.182***	-0.044
	(-11.075)	(-3.868)	(-1.976)	(-9.136)	(-2.556)	(-0.771)
Observations	66,058	17,044	16,914	16,181	10,933	10,841
F 1st st. Cragg-D		106.6	106.9		39.95	35.72
F 1st st. Kleib.-P		14.60	15.50		8.18	9.62
p-val Sargan–H J		0.236	0.295		0.175	0.188
B: ΔEmployment$_{i,t}$						
ΔVolatility$_{i,t-1}$	-0.037***	-0.074***	-0.011	-0.115***	-0.245***	-0.042
	(-12.166)	(-2.684)	(-0.359)	(-10.744)	(-3.353)	(-0.474)
Observations	124,299	28,418	28,120	26,093	17,567	17,380
F 1st st. Cragg-D		157.8	171.2		78.52	58.57
F 1st st. Kleib.-P		18.42	17.46		15.06	11.31
p-val Sargan–H J		0.113	0.506		0.215	0.471
C: ΔCost of Goods Sold$_{i,t}$						
ΔVolatility$_{i,t-1}$	-0.054***	-0.267**	-0.147***	-0.206***	-0.823**	-0.361***
	(-10.114)	(-2.278)	(-3.708)	(-6.009)	(-2.532)	(-3.158)
Observations	125,526	28,471	28,173	26,153	17,596	17,408
F 1st st. Cragg-D		158.4	171.8		78.54	58.56
F 1st st. Kleib.-P		18.43	17.48		14.96	11.16
p-val Sargan–H J		0.143	0.0296		0.193	0.0345

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 (Panel B), and changes in cost of goods sold (Panel C), 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 3. To preserve space we do not report the coefficients and t-statistics on controls. The sample period is annual from 1963 to 2016. Specifications 1,2,4, and 5 are univariate, while 3 and 6 multivariate. Only 1 and 4 are OLS while all others 2SLS. We instrument lagged changes in firm-level volatility with industry-level (3SIC) exposure to 10 aggregate lagged 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) implied volatility of at-the-money-forward call options from OptionMetrics. Regressors lagged by 1-year. Both firm and calendar-year fixed effects are included. Standard errors are clustered at the 3-digit SIC industry. To tease out the impact of 2nd moment uncertainty shocks we also include as controls the lagged exposure to changes in the return on each of the 10 aggregate instruments (i.e., 1st moment shocks). Data availability on implied volatility of treasuries and oil restrict the start of the 2SLS sample to fiscal year 2006. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1, † p<0.15. t-statistics are in parentheses. See section 4 for data details.

Table 6
Financial outcomes

	(1) OLS Realized	(2) IV Realized	(3) IV Realized	(4) OLS Implied	(5) IV Implied	(6) IV Implied
A: ΔTotal Debt$_{i,t}$						
ΔVolatility$_{i,t-1}$	-0.079***	-0.275***	-0.168**	-0.202***	-0.776***	-0.616***
	(-9.669)	(-3.609)	(-2.490)	(-6.794)	(-5.216)	(-3.764)
Observations	124,631	28,298	28,116	25,978	17,473	17,369
F 1st st. Cragg-D		157.1	171.5		77.26	58.32
F 1st st. Kleib.-P		18.29	17.41		14.97	11.18
p-val Sargan–H J		0.131	0.342		0.829	0.865
B: ΔPayout$_{i,t}$						
ΔVolatility$_{i,t-1}$	-0.164***	-0.554***	-0.310***	-0.523***	-1.461***	-0.846***
	(-13.965)	(-4.882)	(-2.656)	(-8.806)	(-4.771)	(-2.656)
Observations	125,538	28,471	28,173	26,153	17,596	17,408
F 1st st. Cragg-D		158.4	171.8		78.54	58.56
F 1st st. Kleib.-P		18.43	17.48		14.96	11.16
p-val Sargan–H J		0.394	0.635		0.990	0.990
C: ΔCash holding$_{i,t}$						
ΔVolatility$_{i,t-1}$	0.030***	0.227***	0.166**	0.117***	0.699***	0.570***
	(3.488)	(3.289)	(2.504)	(3.571)	(4.165)	(2.756)
Observations	125,511	28,468	28,170	26,150	17,593	17,405
F 1st st. Cragg-D		158.4	171.7		78.49	58.53
F 1st st. Kleib.-P		18.44	17.49		14.96	11.17
p-val Sargan–H J		0.545	0.458		0.380	0.345

This table reports regression results of annual changes in total debt (Panel A), changes in firm payout (cash dividend + share repurchase) (Panel B), and changes in cash holdings (cash and short-term investments) (Panel 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 3. To preserve space we do not report the coefficients and t-statistics on controls. The sample period is annual from 1963 to 2016. Specifications 1,2,4, and 5 are univariate, while 3 and 6 multivariate. Only 1 and 4 are OLS while all others 2SLS. We instrument lagged changes in firm-level volatility with industry-level (3SIC) exposure to 10 aggregate lagged 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) implied volatility of at-the-money-forward call options from OptionMetrics. Regressors lagged by 1-year. Both firm and calendar-year fixed effects are included. Standard errors are clustered at the 3-digit SIC industry. To tease out the impact of 2nd moment uncertainty shocks we also include as controls the lagged exposure to changes in the return on each of the 10 aggregate instruments (i.e., 1st moment shocks). Data availability on implied volatility of treasuries and oil restrict the start of the 2SLS sample to fiscal year 2006. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1, † p<0.15. t-statistics are in parentheses. See section 4 for data details.

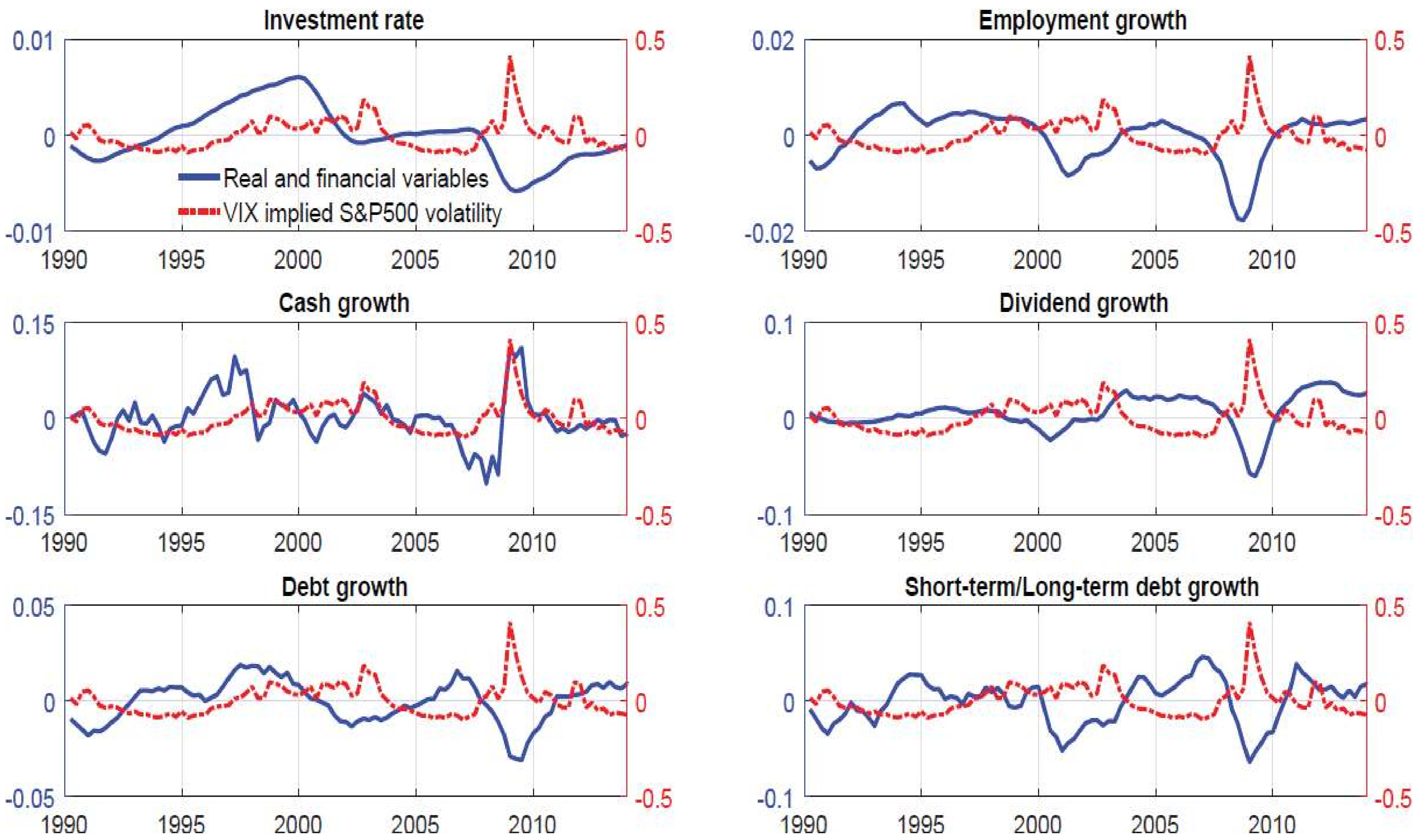
Table 7

Impact of realized volatility on investment for financially constrained and unconstrained firms during financial crisis and non-crisis years

Crisis period: Jan-01-2008 to Dec-31-2009	2SLS with full set of controls (1-8)							
Investment Rate$_t$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Financial Constraint Measure			S&P Ratings	Whited-Wu	Employees	Assets	Age	Size&Age
ΔVolatility$_{i,t-1}$ (Realized)	-0.030***	-0.013	-0.010	-0.025**	-0.025**	-0.022**	-0.021**	-0.017*
$D_{crisis,t}$		-	-	-	-	-	-	-
$D_{crisis,t} \cdot \Delta$Volatility$_{i,t-1}$		-0.091***	-0.074***	-0.068***	-0.064***	-0.104***	-0.060**	-0.091***
$D_{fin\_constrained,i,t-1}$			-0.005*	0.009	0.011	-0.002	-	-0.027
$D_{fin_constrained,i,t-1} \cdot \Delta$Volatility$_{i,t-1}$			-0.008	0.018	0.021†	0.009	0.002	0.016
$D_{crisis,t} \cdot D_{fin\_constrained,i,t-1}$			0.003	-0.010†	-0.012*	-0.015**	-0.000	-0.011**
$D_{crisis,t} \cdot D_{fin_constrained,i,t-1} \cdot \Delta$Volatility$_{i,t-1}$			-0.028	-0.052**	-0.055***	-0.043*	-0.013	-0.047**
Observations	28,132	28,132	28,132	21,132	21,138	21,132	22,131	21,153
F-test 1st stage Cragg-D	171.1	88.48	43.34	29.46	37.26	24.05	36.52	28.86
F-test 1st stage Kleib.-P.	17.57	6.25	4.16	4.26	9.55	5.34	3.35	5.63
p-val Sargan–Hansen J	0.955	0.789	0.531	0.369	0.844	0.721	0.945	0.495

Table presents the impact of exogenous firm-level realized volatility on investment rates of financially constrained and unconstrained firms during financial crisis and non-crisis years. All regressions are 2SLS of investment rate - observed at fiscal year t and defined as I_t/K_{t-1} (capx/lagged net property plant & equipment from Compustat)- on 1-year lagged changes in firm-level realized volatility and a full set of lagged firm-level controls. All specifications follow the setup, timing, and controls included in specification (3) in Table 3. Column 1 restates the benchmark regression (3) in Table 3. Column 2 further adds the interaction of lagged change in realized volatility with a financial-crisis dummy variable that takes value 1 for all firm-fiscal-year observations of investment rate ending in between Jan. 1 2008 and Dec. 31 2009, zero otherwise. This period comprises the great recession. Columns 3 to 8 run further interact lagged changes in volatility with standard measures of financial constraints and the crisis dummy. In particular, using each firm's financial constraint index at every fiscal year $t-1$ we classify firms into constrained and unconstrained groups using the 40 and 60 percentile cutoffs obtained from the cross-sectional fiscal-year distribution of the underlying financial constraint index. We consider a firm constrained if its $t-1$ index value is equal to or greater than the 60 percentile and unconstrained if equal to or less than the 40 percentile. We exclude firm-time observations in the middle 50+/-10 percentiles to increase precision in the classification of firms. We do this in all but the S&P credit-rating financial constraint measure. 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). The other 5 measures of financial constraints are constructed using the Whited-Wu index, reciprocal of employees, reciprocal of total assets, reciprocal of age, and the SA index based on size and age of Hadlock and Pierce (2010). Both firm and calendar-year fixed effects are included. Standard errors are clustered at the 3 digit SIC industry. Data availability on implied volatility of treasuries and oil restrict the start of the 2SLS sample to fiscal year 2006. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1, † p<0.15. t-statistics in parentheses. See sections 4 for data details.

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). Short-term debt sum of open market paper (line 123) and short-term loans (line 127). Long-term debt sum of bonds (line 125) and mortgages (line 130). Cash sum of currency and transferable deposits (line 97) and time and savings deposits (line 98). 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.

Figure 2: Investment and Payout Policy Functions

Figure 2A: Real fixed costs only

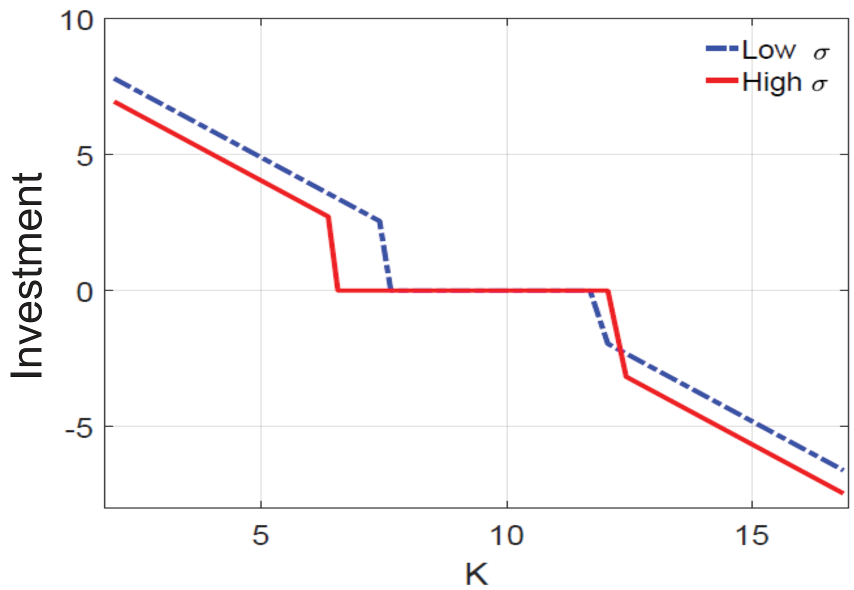


Figure 2B: Benchmark: real and financial fixed costs

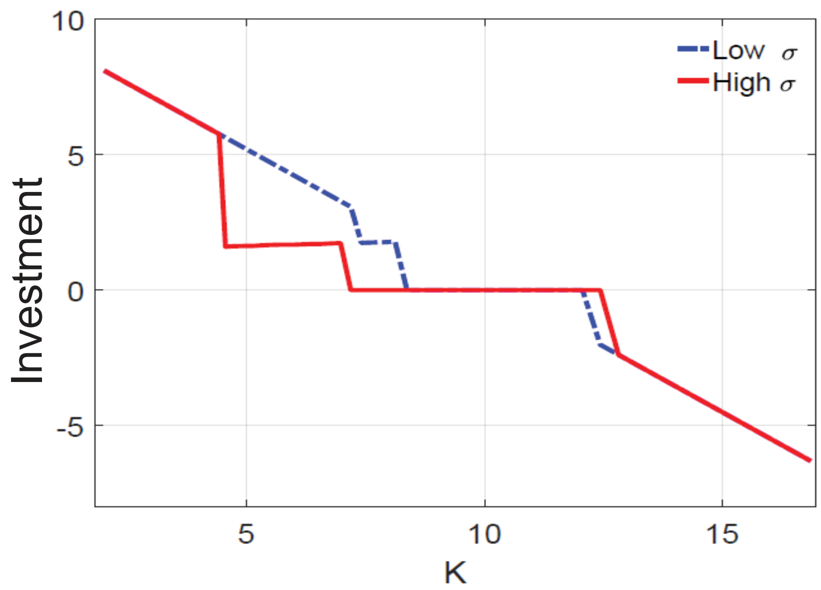
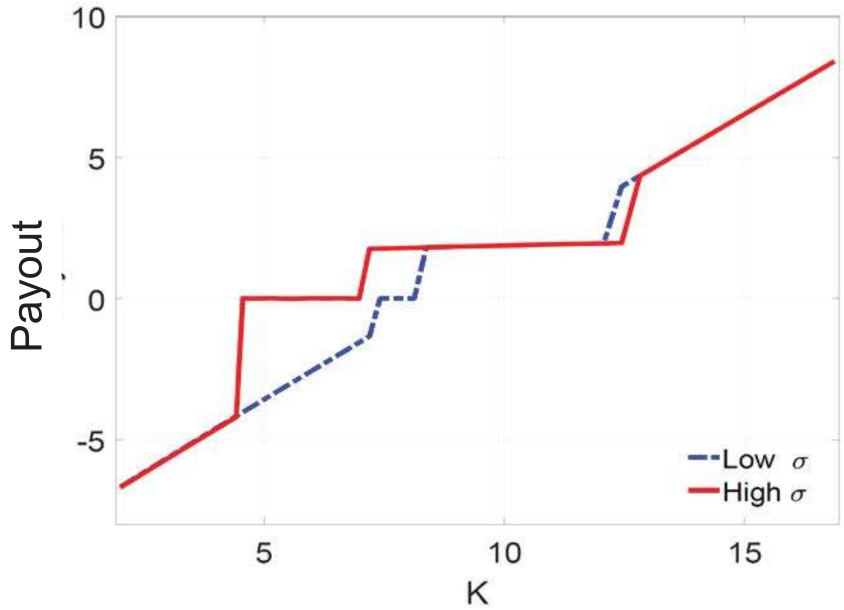
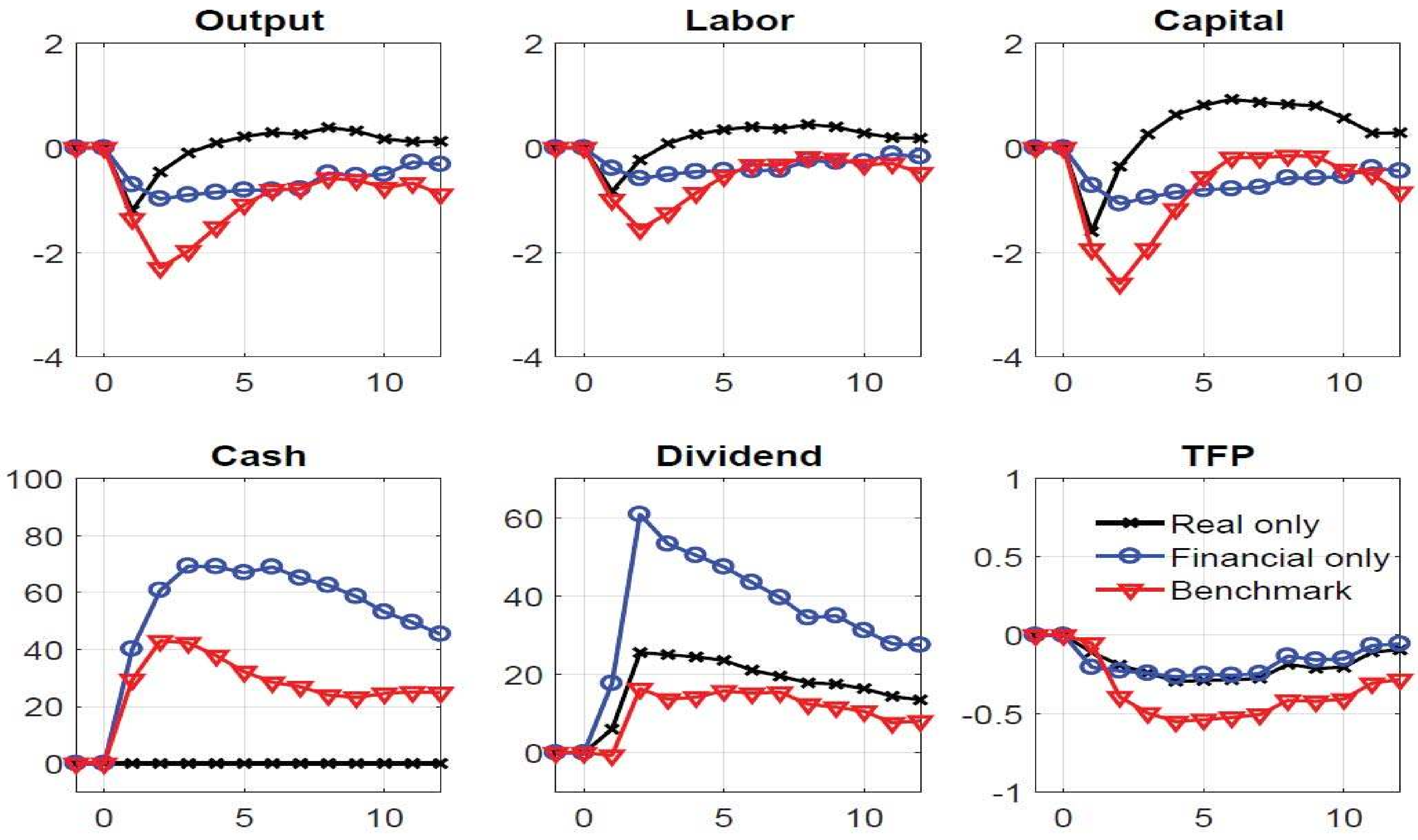


Figure 2C: Benchmark: real and financial fixed costs



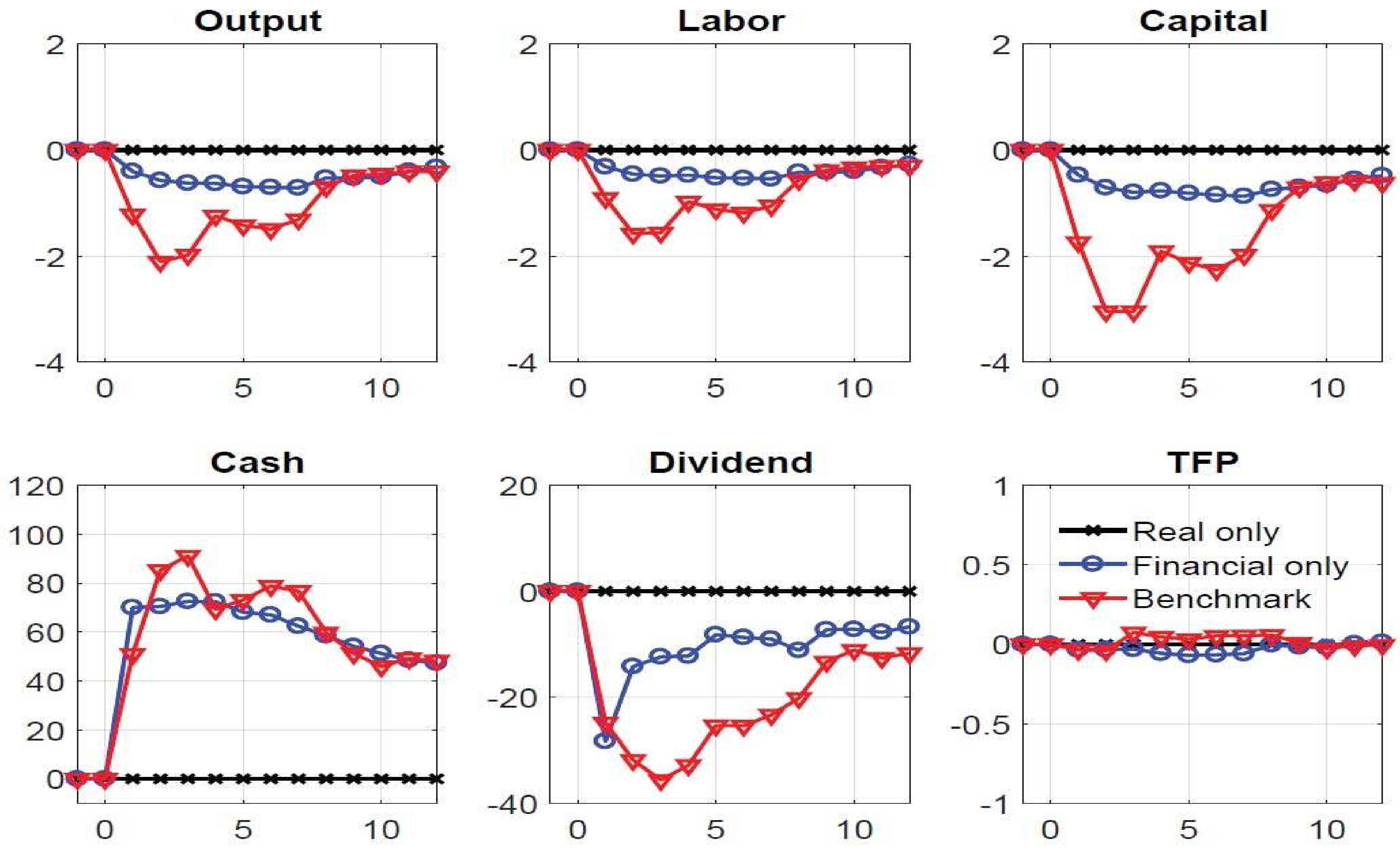
Notes: Figures 2A and 2B plot the optimal investment policies associated with low and high uncertainty shock states of the model with real investment costs only (top left) and the benchmark model (top right), respectively. In both figures, we fix the idiosyncratic productivity and cash at their median grid points and the financial shock at the low state. Figure 2C plots the payout of the benchmark model (bottom left) with low and high uncertainty by fixing the idiosyncratic productivity and cash at their median grid points and the financial shock at its low states.

Figure 3: The Impact of a pure Uncertainty Shock



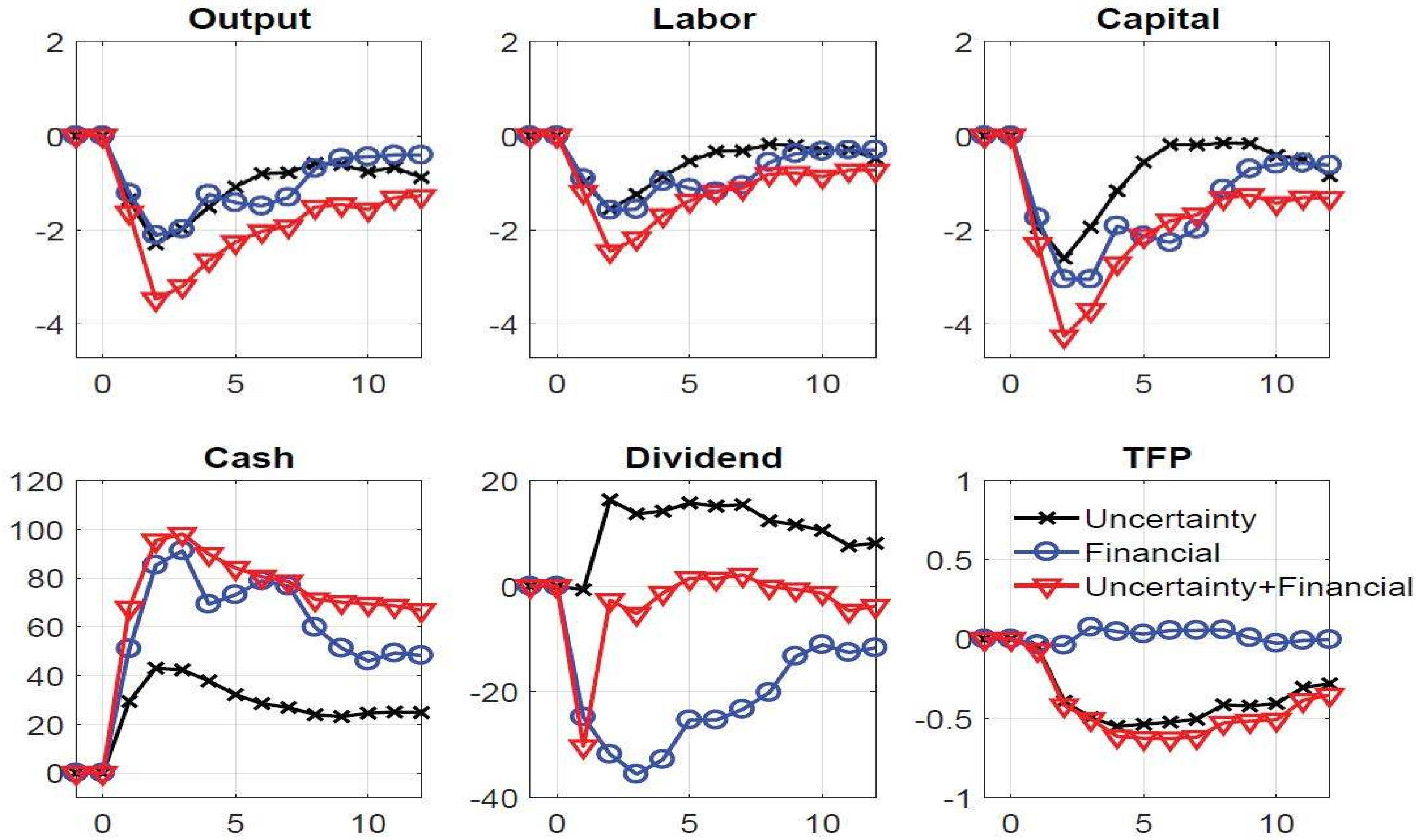
Notes: We plot the percent deviations of average output, labor, capital, cash, dividend and aggregate TFP from their values in quarter 0 of three model specifications: i) the model with real cost only (black x-mark); ii) the model with financial cost only (blue circle), and iii) the benchmark with both 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 4: The Impact of a pure Financial Shock



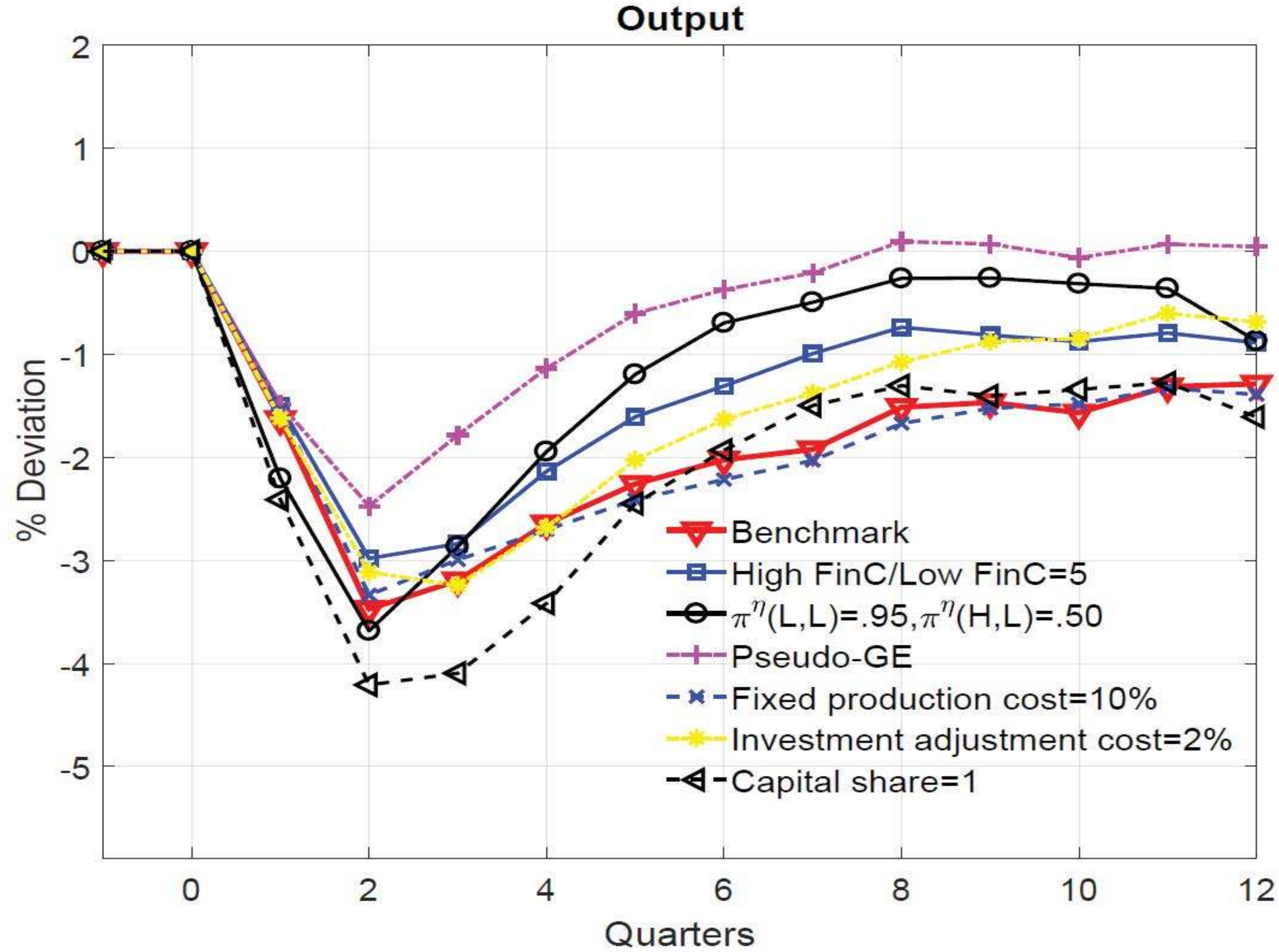
Notes: We plot the percent deviations of average output, labor, capital, cash, dividend and aggregate TFP from their values in quarter 0 of three model specifications: i) the model with real cost only (black x-mark); ii) the model with financial cost only (blue circle), and iii) the benchmark with both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

Figure 5: The Impact of Uncertainty and Financial Shocks



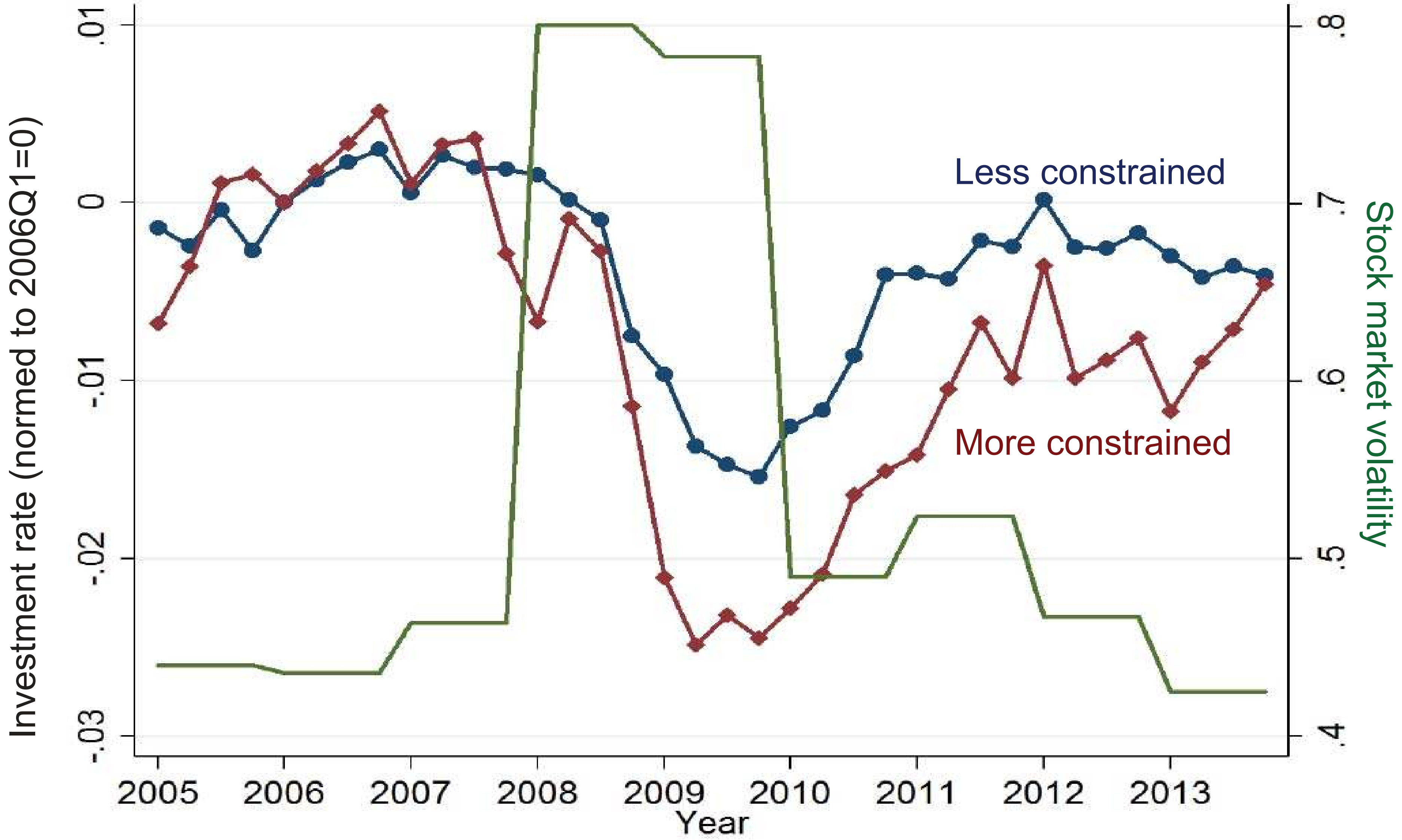
Notes: We plot the percent deviations of average output, labor, capital, cash, dividend and aggregate TFP from their values in quarter 0 of the benchmark model with both real and financial costs. All plots are based on simulations of 30,000 firms of 1000-quarter length. We impose an uncertainty shock (black x-mark), a financial shock (blue circle) and a combined uncertainty and financial shocks (red triangle) 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 high financing-cost-state-to-low-cost-state ratio at 5 (blue-square), the model with a different transition matrix of financial shocks (black-circle), the pseudo-GE model (magenta-plus), the model with fixed production cost at 10% (blue-dashed-cross), the model with investment adjustment cost at 2% (yellow-star) and the model with the capital share at 1 (black-dashed-triangle). All plots are based on simulations of 30,000 firms of 1000-quarter length. We impose a combined uncertainty and financial shocks in the quarter labelled 1, allowing normal evolution of the economy afterwards.

Figure 7: Investment by more and less financially constrained firms



Notes: Plots the investment rate for financially more-constrained firms (red line, diamond markers) and less-constrained firms (blue line, circle markers) against the left axis. Financial constraints defined as a firm having short or long term debt but no bond rating (see Duchin, Ozbas and Sensoy, JFE 2010 and Faulkender and Petersen, RFS 2006). Stock-market volatility (green line, no-markers) plots the average volatility of all firms in the sample by year, right axis.

Appendix For Online Publication

A Numerical algorithm

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 312 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 Data

Data used in the empirical analysis is described in detail in this section. Sources include Compustat, CRSP, OptionMetrics, Bloomberg, CBOE, St. Louis Fed, and Baker, Bloom, and Davis (2016). Table A2 presents descriptive statistics of main variables used in the firm-level panel regressions. Our annual sample period begins in 1963 and ends in 2016.[25]

B.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.[26] When

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

[26] 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

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 as $SG\&A + R\&D$ (sales, general and administration plus research and development), and cost of goods sold, $COGS$. 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

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.

the annual volatility of the firm's realized CRSP stock return. Specifically, we estimate it as the 12-month fiscal-year standard deviation of daily CRSP returns. We annualize this standard deviation by multiplying by the square root of 252 (average trading days in a year). This makes the standard deviation comparable to the annual volatility implied by call options, which we describe in the next subsection. 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).

B.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.

B.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 the exchange rates between the U.S. dollar and the 7 "major" currencies used by the Board in constructing the nominal and real trade-weighted U.S. dollar Index of Major Currencies[27].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. These daily currency spot prices are used in the daily regression described in equation 14 .

In addition to the daily currency prices, our instrumental variables approach further requires measures of forward-looking implied volatility for each of the 7 currencies. For these we use daily data on three-month implied exchange rate volatilities for each bilateral rate, from Bloomberg. Specifically, we extract these data using the VOLC function available at Bloomberg terminals.

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

B.4 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 from Bloomberg. In particular, Bloomberg provides price and 30-day implied volatility data for one-month crude oil futures. Specifically, we use data on the New York Mercantile Exchange Division's light, sweet crude oil futures contract (Bloomberg CL1). 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 1Q 2003.

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.

B.5 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,$\mid \beta_j^{c,weighted} \mid \cdot\Delta\sigma_{t-1}^c$, and also our main uncertainty measure of the lagged growth in firm $i's$ realized annual volatility, $\Delta\sigma_{i,t-1}$. 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 $IV_{t-1}^c = \mid \beta_j^{c,weighted} \mid \cdot\Delta\sigma_{t-1}^c$ 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 $\mid \beta_j^{c,weighted} \mid$ is the significance-weighted cross-industry exposure estimated 36 months prior to the firm's fiscal-year end month of the dependant variable, $\Delta y_{i,t}$.

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 2006. Our sample ends in December 2016.

Table A1

Coefficient on changes in volatility for real and financial variables

	Real		**Financial**	
	I/K	ΔEmp	ΔCash	Div/K
A: Benchmark				
ΔVolatility	-0.080	-0.028	0.487	-0.012
B: H/L = 5				
ΔVolatility	-0.090	-0.031	0.462	-0.007
C: Different transition matrix of η_t				
ΔVolatility	-0.086	-0.030	0.465	-0.009
D: Pseudo-GE				
ΔVolatility	-0.053	-0.020	0.610	-0.020
E: F = 0.10				
ΔVolatility	-0.071	-0.025	0.820	-0.018
F:c_k= **0.02**				
ΔVolatility	-0.093	-0.031	0.169	-0.004
G:$\alpha = 1$				
ΔVolatility	-0.086	na	-0.082	-0.002

This table reports the model regression results of real and financial variables on volatility growth. The reported statistics in the model are from simulated data with 3000 firms and 200 quarterly observations. We report the cross-simulation averaged annual moments. I/K is the investment rate, ΔEmp is the employment growth, ΔCash is the cash growth rate, and Div/K is the ratio of dividend to capital in the model and cash dividend plus repurchase to total assets in the data. Panel A is the benchmark calibration. Panels B lowers the high financing-cost-state-to-low-cost-state ratio (η_H/η_L) to 5 while keeping the low financial cost state $\eta_L = 0.005$. Panel C sets the transition probabilities of financial shocks of $\pi^{\sigma}_{L,H} = 0.05$ and $\pi^{\sigma}_{H,H} = 0.5$. Panel D is the pseudo-GE model with interest rates, prices and wages as functions of uncertainty shock. Panel E is the model with smaller fixed production cost $F = 0.10$. Panel F is the model with bigger investment adjustment cost $c_k = 0.02$. Panel G is the model with the share of capital $\alpha = 1$. All the regressions include firm and time fixed effects and all results for the model are significant at the 1% level with firm-clustered standard errors.

Table A2
Descriptive statistics

Variables in 2SLS	Obs.	Mean	S. Dev	P1	P10	P50	P90	P99
Dependent								
Investment Rate	125,596	0.248	0.152	0.012	0.067	0.215	0.500	0.500
ΔEmployment	125,690	0.026	0.231	-0.765	-0.192	0.021	0.258	0.744
ΔIntangible Cap. Invest.	66,977	0.077	0.198	-0.535	-0.137	0.077	0.292	0.642
ΔCost of Goods Sold	126,913	0.080	0.283	-0.929	-0.177	0.080	0.342	1.024
ΔDebt Total	126,022	0.046	0.669	-2.000	-0.514	0.000	0.738	2.000
ΔPayout	126,925	0.066	0.919	-2.000	-1.185	0.000	1.482	2.000
ΔCash Holdings	126,899	0.043	0.702	-1.727	-0.839	0.043	0.934	1.797
Independent								
ΔRealized Volatility	126,925	-0.001	0.303	-0.673	-0.376	-0.012	0.386	0.780
ΔImplied Volatility	26,759	-0.015	0.200	-0.435	-0.259	-0.026	0.247	0.513
Book Leverage	125,460	0.322	0.279	0.000	0.000	0.291	0.672	1.287
Stock Return	126,925	0.176	0.674	-0.765	-0.458	0.066	0.847	2.781
Log Sales	126,680	5.092	2.140	-0.246	2.452	5.043	7.887	9.979
Return on Assets	126,914	0.049	0.181	-0.784	-0.108	0.082	0.194	0.326
Tangibility	126,545	0.550	0.363	0.037	0.140	0.479	1.057	1.657
Tobin's Q	125,795	1.482	0.833	0.569	0.791	1.215	2.539	4.690
Instruments								
ΔVol Exposure Cad	44,220	3e-04	0.006	-0.015	-0.001	0.000	0.002	0.020
ΔVol Exposure Euro	43,773	-2e-04	0.011	-0.030	-0.004	0.000	0.001	0.047
ΔVol Exposure Jpy	50,607	1e-04	0.005	-0.011	-0.001	0.000	0.000	0.015
ΔVol Exposure Aud	50,607	3e-05	0.006	-0.018	-0.003	0.000	0.003	0.022
ΔVol Exposure Sek	44,220	2e-04	0.007	-0.021	-0.004	0.000	0.002	0.032
ΔVol Exposure Chf	50,607	1e-04	0.009	-0.021	-0.003	0.000	0.001	0.032
ΔVol Exposure Gbp	50,607	1e-04	0.005	-0.014	-0.001	0.000	0.000	0.018
ΔVol Exposure Oil	29,016	6e-05	0.011	-0.040	-0.001	0.000	0.001	0.029
ΔVol Exposure Policy	50,607	3e-07	2e-05	-8e-05	0.000	0.000	0.000	8e-05
ΔVol Expos.Treasury	29,195	-0.637	8.503	-32.100	-4.564	0.000	2.286	26.640

This table presents summary statistics of all main variables used in the empirical panel 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, Bloomberg, CBOE, St. Louis Fed, and Baker, Bloom, and Davis (2016). See sections 4 and 5 for the details on the construction of variables.

Table A3
2SLS Sensitivity to individual instruments

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
IV Dropped	None	Cad	Euro	Jpy	Aud	Sek	Chf	Gbp	Policy	Oil+Treasuries
Real Variables										
Investment $\text{Rate}_{i,t}$	-0.030***	-0.032***	-0.029***	-0.030***	-0.034***	-0.035***	-0.030***	-0.030***	-0.031***	-0.036**
ΔIntang. Cap. $\text{Invest.}_{i,t}$	-0.036**	-0.035*	-0.034*	-0.038**	-0.040**	-0.030†	-0.042**	-0.040**	-0.033*	-0.035†
$\Delta\text{Employment}_{i,t}$	-0.011	-0.009	-0.008	-0.011	-0.010	-0.037	-0.017	-0.010	-0.009	0.016
Financial Variables										
ΔDebt $\text{Total}_{i,t}$	-0.168**	-0.154**	-0.156**	-0.167**	-0.200***	-0.203***	-0.163**	-0.168**	-0.170**	-0.218**
$\Delta\text{Payout}_{i,t}$	-0.310***	-0.331***	-0.291***	-0.306***	-0.379***	-0.286**	-0.274**	-0.303**	-0.302**	-0.487***
ΔCash $\text{Holdings}_{i,t}$	0.166**	0.153**	0.164**	0.159**	0.202***	0.175**	0.124*	0.157**	0.161**	0.265**
1st moment $10\text{IV}_{i,t-1}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm, time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE cluster (3SIC)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Investment Rate Stats										
Observations	28,132	28,132	28,132	28,132	28,132	28,132	28,132	28,132	28,132	42,388
F 1st stage Cragg-D	171.1	178.7	182.8	187.5	161.6	150.8	173	182.4	184.9	99.17
F 1st stage Kleib.-P.	17.57	19.84	19.35	18.34	14.09	17.88	18.40	16.97	18.31	12.09
p-val Sargan–Hans J	0.955	0.946	0.939	0.921	0.961	0.950	0.921	0.938	0.920	0.992

This table presents 2SLS multivariate regression results for all our main real and financial outcome variables (with full set of controls) when we drop individual instruments one at a time from our benchmark set of 10 instrumental variables (IVs). In the last column (10) we drop both oil and treasury IVs as these constrain the start of the sample to fiscal year 2006, whereas keeping only currencies and policy IVs allow an additional 4 years of panel data -with first fiscal year of dependent variable starting in 2002. Sample period ends in December 2016. The coefficient and statistics reported in (1) are from the benchmark 2SLS multivariate regression on lagged firm-level realized volatility shocks presented in column (3) across Tables 3, 5, and 6. The statistics under "Investment Rate Stats" correspond to the 1st stage results of the multivariate 2SLS regression of investment rate on lagged change in realized volatility and main set of lagged level controls. 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 included. Standard errors clustered at the 3 digit SIC industry. To tease out the impact of 2nd moment uncertainty shocks we also include as controls the lagged exposure to the return on each of the 10 aggregate instruments (i.e., 1st moment shocks). Data availability on implied volatility of treasuries and oil restrict the start of the 2SLS sample to fiscal year 2006. Statistical significance: *** $p<0.01$, ** $p<0.05$, * $p<0.1$, † $p<0.15$. *t*-statistics are in parentheses. See section 4 for data details.

Table A4
2SLS Robustness tests

	(1)	(2)	(3)	(4)	(5)	(1A)	(2A)	(3A)	(4A)	(5A)
Volatility Instrumented	Realized	Realized	Realized	Realized	Realized	Implied	Implied	Implied	Implied	Implied
Real Variables										
Investment Rate$_{i,t}$	-0.033***	-0.030***	-0.030***	-0.031***	-0.030***	-0.082*	-0.077**	-0.083**	-0.081**	-0.083**
ΔIntangible Cap. Invest.$_{i,t}$	-0.042**	-0.034*	-0.032*	-0.033*	-0.029†	-0.079	-0.036	-0.044	-0.036	-0.026
ΔEmployment$_{i,t}$	-0.005	-0.010	-0.012	-0.011	-0.011	0.045	-0.039	-0.046	-0.045	-0.041
Financial Variables										
ΔDebt Total$_{i,t}$	-0.184**	-0.167**	-0.170**	-0.169**	-0.168***	-0.843***	-0.602***	-0.623***	-0.620***	-0.612***
ΔPayout$_{i,t}$	-0.358**	-0.295**	-0.333***	-0.313***	-0.320***	-1.419**	-0.798**	-0.927***	-0.847***	-0.877***
ΔCash Holdings$_{i,t}$	0.183**	0.160**	0.154**	0.164**	0.151**	0.818**	0.567***	0.582***	0.569***	0.579***
Leverage-adjusted ΔVolatility$_{i,t-1}$	Yes					Yes				
Main firm-level controls$_{i,t-1}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	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	28,078	28,132	28,058	28,132	28,058	17,358	17,391	17,345	17,391	17,345
F 1st stage Cragg-Donald Wald	96.72	182.6	170.3	171	181.8	12.52	64.9	58.17	59.06	65.05
F 1st stage Kleibergen-Paap Wald	14.30	19.39	17.50	17.61	19.32	4.89	13.04	11.38	11.28	13.31
p-val Sargan–Hansen J Chi-sq	0.891	0.955	0.928	0.950	0.922	0.846	0.949	0.938	0.950	0.934

This table presents 2SLS robustness results for all our real and financial outcome variables examined in main Tables 3, 5, and 6. 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, 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. 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. t-statistics are in parentheses. See section 4 for data details.

Table A5

Investment rate, using same panel across specifications

Investment rate$_{i,t}$	(1) OLS Realized	(2) IV Realized	(3) IV Realized	(4) OLS Implied	(5) IV Implied	(6) IV Implied
ΔVolatility$_{i,t-1}$	-0.033***	-0.086***	-0.029**	-0.079***	-0.225***	-0.078**
	(-4.642)	(-3.527)	(-2.470)	(-7.447)	(-4.184)	(-2.454)
Book Leverage$_{i,t-1}$			-0.040***			-0.037***
			(-6.203)			(-5.583)
Stock Return$_{i,t-1}$			0.006**			0.005*
			(2.194)			(1.808)
Log Sales$_{i,t-1}$			-0.023***			-0.022***
			(-5.419)			(-5.290)
Return on Assets$_{i,t-1}$			0.138***			0.132***
			(4.087)			(3.910)
Tangibility$_{i,t-1}$			-0.126***			-0.123***
			(-3.491)			(-3.355)
Tobin's Q$_{i,t-1}$			0.055***			0.054***
			(8.089)			(8.341)
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	17,391	17,391	17,391	17,391	17,391	17,391
F 1st st. Cragg-D		131.5	140.1		77.94	58.59
F 1st st. Kleib.-P		15.40	15.29		14.99	11.14
p-val Sargan–H J		0.590	0.918		0.659	0.950

This table presents all investment rate regression results shown in main Table 3 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 and 4 are OLS while all others 2SLS. We instrument lagged changes in firm-level volatility with industry-level (3SIC) exposure to 10 aggregate lagged uncertainty shocks. These include the lagged exposure to annual changes in expected volatility of energy, currencies, and 10-year treasuries 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) implied volatility of at-the-money-forward call options from OptionMetrics. Regressors lagged by 1-year. Both firm and calendar-year fixed effects are included. Standard errors are clustered at the 3-digit SIC industry. To tease out the impact of 2nd moment uncertainty shocks we also include as controls the lagged exposure to changes in the return on each of the 10 aggregate instruments (i.e., 1st moment shocks). Data availability on implied volatility of treasuries and oil restrict the start of the 2SLS sample to fiscal year 2006. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1, † p<0.15. t-statistics are in parentheses. See section 4 for data.

Table A6

Uncertainty effects on corporate dividend payout ratios

Payout ratio$_{i,t}$	(1) OLS Realized	(2) IV Realized	(3) IV Realized	(4) OLS Implied	(5) IV Implied	(6) IV Implied
ΔVolatility$_{i,t-1}$	-0.004***	-0.019***	-0.009*	-0.016***	-0.059***	-0.037**
	(-10.734)	(-3.893)	(-1.658)	(-6.650)	(-4.237)	(-2.072)
Book Leverage$_{i,t-1}$			-0.029***			-0.036***
			(-4.028)			(-3.226)
Stock Return$_{i,t-1}$			-0.003***			-0.005***
			(-5.102)			(-3.966)
Log Sales$_{i,t-1}$			0.002			0.004
			(0.876)			(0.850)
Return on Assets$_{i,t-1}$			0.034***			0.036***
			(4.585)			(3.019)
Tangibility$_{i,t-1}$			-0.006			0.002
			(-1.186)			(0.261)
Tobin's Q$_{i,t-1}$			0.014***			0.018***
			(5.593)			(4.268)
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	125,532	28,471	28,173	26,153	17,596	17,408
F 1st st. Cragg-D		158.4	171.8		78.54	58.56
F 1st st. Kleib.-P		18.43	17.48		14.96	11.16
p-val Sargan–H J		0.542	0.326		0.338	0.262

Table presents OLS and 2SLS annual regression results of firm corporate dividend payout ratios on 1-year lagged changes in firm-level volatility and lagged level of firm-level controls. Dividend payout ratio at fiscal year t is defined as $\frac{Payout_{i,t}}{AT_{i,t-1}}$, where $Payout = DV + PRSTKC$, DV is cash dividends and $PRSTKC$ is purchase of common and preferred stock, and AT is total assets from Compustat. Sample period is from 1963 to 2016. Specifications 1 and 4 are OLS while all others 2SLS. We instrument lagged changes in firm-level volatility with industry-level (3SIC) exposure to 10 aggregate lagged uncertainty shocks. These include the lagged exposure to annual changes in expected volatility of energy, currencies, and 10-year treasuries 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) implied volatility of at-the-money-forward call options from OptionMetrics. Regressors lagged by 1-year. Both firm and calendar-year fixed effects are included. Standard errors are clustered at the 3-digit SIC industry. To tease out the impact of 2nd moment uncertainty shocks we also include as controls the lagged exposure to changes in the return on each of the 10 aggregate instruments (i.e., 1st moment shocks). Data availability on implied volatility of treasuries and oil restrict the start of the 2SLS sample to fiscal year 2006. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1, † p<0.15. t-statistics are in parentheses. See section 4 for data.

Table A7
Impact of implied volatility on investment for financially constrained and unconstrained firms during financial crisis and non-crisis years

Crisis period: Jan-01-2008 to Dec-31-2009	2SLS with full set of controls (1-8)							
Investment Rate$_t$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Financial Constraint Measure			S&P Ratings	Whited-Wu	Employees	Assets	Age	Size&Age
ΔVolatility$_{i,t-1}$ (Implied)	-0.078**	-0.048†	-0.043†	-0.060**	-0.071**	-0.053**	-0.060*	-0.055**
$D_{crisis,t}$		-	-	-	-	-	-	-
$D_{crisis,t} \cdot \Delta$Volatility$_{i,t-1}$		-0.093*	-0.084*	-0.027	-0.075	-0.075	-0.057	-0.077
$D_{fin\_constrained,i,t-1}$			-0.005	0.004	0.039†	0.018	-	-0.124**
$D_{fin_constrained,i,t-1} \cdot \Delta$Volatility$_{i,t-1}$			-0.021	0.110***	0.068	0.057*	0.014	0.060**
$D_{crisis,t} \cdot D_{fin\_constrained,i,t-1}$			0.003	0.003	-0.010	-0.010	0.001	-0.012†
$D_{crisis,t} \cdot D_{fin_constrained,i,t-1} \cdot \Delta$Volatility$_{i,t-1}$			-0.014	-0.170***	-0.151***	-0.083*	-0.025	-0.104**
Observations	17,391	17,391	17,391	12,977	13,261	12,942	13,849	12,832
F-test 1st stage Cragg-D	58.59	32.99	16.84	12.60	14.56	14.32	12.86	12.94
F-test 1st stage Kleib.-P.	11.14	10.31	7.10	8.54	7.82	7.91	5.57	7.82
p-val Sargan–Hansen J	0.950	0.994	0.985	0.621	0.713	0.637	0.754	0.219

Table presents the impact of exogenous firm-level implied volatility on investment rates of financially constrained and unconstrained firms during financial crisis and non-crisis years. All regressions are 2SLS of investment rate - observed at fiscal year t and defined as I_t/K_{t-1} (capx/lagged net property plant & equipment from Compustat)- on 1-year lagged changes in firm-level implied volatility and a full set of lagged firm-level controls. All specifications follow the setup, timing, and controls included in specification (6) in Table 3. Column 1 restates the benchmark regression (6) in Table 3. Column 2 further adds the interaction of lagged change in realized volatility with a financial-crisis dummy variable that takes value 1 for all firm-fiscal-year observations of investment rate ending in between Jan. 1 2008 and Dec. 31 2009, zero otherwise. This period comprises the great recession. Columns 3 to 8 run further interact lagged changes in volatility with standard measures of financial constraints and the crisis dummy. In particular, using each firm's financial constraint index at every fiscal year $t-1$ we classify firms into constrained and unconstrained groups using the 40 and 60 percentile cutoffs obtained from the cross-sectional fiscal-year distribution of the underlying financial constraint index. We consider a firm constrained if its $t-1$ index value is equal to or greater than the 60 percentile and unconstrained if equal to or less than the 40 percentile. We exclude firm-time observations in the middle 50+/-10 percentiles to increase precision in the classification of firms. We do this in all but the S&P credit-rating financial constraint measure. 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). The other 5 measures of financial constraints are constructed using the Whited-Wu index, reciprocal of employees, reciprocal of total assets, reciprocal of age, and the SA index based on size and age of Hadlock and Pierce (2010). Both firm and calendar-year fixed effects are included. Standard errors are clustered at the 3 digit SIC industry. Data availability on implied volatility of treasuries and oil restrict the start of the 2SLS sample to fiscal year 2006. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1, † p<0.15. t-statistics in parentheses. See sections 4 for data details.