The Finance Uncertainty Multiplier*

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December 29, 2017

Abstract

We show how real and financial frictions amplify the impact of uncertainty shocks. We start by building a model with real frictions, and show how adding financial frictions roughly doubles the negative impact of uncertainty shocks. The reason is higher uncertainty alongside financial frictions induces the standard negative real-options effects on the demand for capital and labor, but also leads firms to hoard cash against future shocks, 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 factor price volatility. Consistent with the model we find that higher uncertainty reduces firms' investment, hiring, while increasing their cash holdings and cutting their dividend payouts, particularly for financially constrained firms. This highlights why in periods with greater financial frictions – like during the global-financial-crisis – uncertainty can be particularly damaging.

JEL classification: D22, E23, E44, G32
Keywords: Uncertainty, Financial frictions, Investment, Employment, Cash holding, Equity payouts

*We would like to thank our formal discussants Nicolas Crouzet, Ian Dew-Becker, Simon Gilchrist, Po-Hsuan Hsu, Gill Segal, Toni Whited, and the seminar audiences at the AEA, AFA, Beijing University, CEIBS, Econometric Society, European Finance Association, Macro Finance Society Workshop, Melbourne Institute Macroeconomic Policy Meetings, Midwest Finance Association, Minneapolis Fed, NY Fed, Stanford SITE, The Ohio State University, UBC Summer Finance Conference, University College London, University of North Carolina at Chapel Hill, University of St. Andrews, University of Texas at Austin, University of Texas at Dallas, University of Toronto, Utah Winter Finance Conference, World Congress. The NSF and Alfred Sloan Foundation kindly provided research support.

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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 Trump election - are accompanied by steady 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 2.4%, but with *only* real frictions a drop of 1.3%. In a slightly abusive notation, where Y is output, σ is uncertainty, and FC is financial adjustment costs, $FUM = \frac{d^2Y}{d\sigma dFC} \approx -2$, i.e., 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 2.4%, but jointly reduce output by 4%.

We summarize these two results below in table 1. This reports the peak drop in aggregate output in our calibrated model with only real frictions and an uncertainty shock is 1.3% (top left

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

[2] See, for example, Gomes [2001], Hennessy and Whited [2005], Hennessy and Whited [2007], Bolton et al. [2013], etc.

box). Adding financial frictions almost doubles the size of this drop to 2.4% (bottom left box). Finally, adding a financial shock increases the impact by another two-thirds, yielding a drop in output of 4.0% (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.

Table 1
Key results in simulation

	Uncertainty shock	Uncertainty + financial shocks
Real frictions	1.3%	n/a
Real+financial frictions	2.4%	4.0%

Notes: Results based on simulations of 30,000 firms of 1000-quarter length in the calibrated model (see section 3.4.1). Going from top to bottom row shows adding financial frictions roughly doubles the impact of uncertainty shocks (a FUM is around 2). Going from the left to right column shows the additive impact of uncertainty shocks and financial shocks in models with both real and financial frictions.

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 shows 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 - which we model in an extension of our baseline model - 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 in the model 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 real wages and interest rates to move after uncertainty shocks following typical changes observed in the data, and find our results are about 1/3 smaller but qualitatively similar.[3] Finally, we ignore debt financing (only allowing for equity financing), since this would dramatically increase the complexity of the financial modeling (but with probably limited impact on the real-side of the model). In an extension with debt rather than equity we show uncertainty shocks generate similar results.

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 debt, dividends 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 the

[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 et al. [2016]).

[4] See, for example, Nieuwerburgh and Veldkamp [2006], Bachmann and Moscarini [2012], Pastor and Veronesi [2012], Orlik and Veldkamp [2015], Berger et al. [2016], and Falgelbaum et al. [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 et al. [2011], Fernandez-Villaverde et al. [2015], and Christiano et al. [2014]. Several other papers look at uncertainty shocks - for example, Bansal and Yaron [2004] and Segal et al. [2015] look at the consumption and financial implications of uncertainty, Handley and Limao [2012] at uncertainty and trade, Ilut and Schneider [2014] model ambiguity aversion as an alternative to stochastic volatility, and Basu and Bundick [2017] examine uncertainty

literature to show the joint importance of real and financial frictions for investment, 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.

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shocks in a sticky-price Keynesian model, and Berger et al. [2016] on 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]).

[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, Jermann and Quadrini [2012], Christiano et al. [2014], and Gilchrist et al. [2014], Arellano et al. [2016], show that financial frictions are important to explain the aggregate fluctuations for the recent financial crisis.

[7] For example, Rajan and Zingales [1995], Welch [2004], Moyen [2004], Hennessy and Whited [2005], Riddick and Whited [2009], DeAngelo et al. [2011], Bolton et al. [2011], Rampini and Viswanathan [2013], Chen et al. [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),

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

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 $Z_t^{1-a-b} = \widetilde{Z}_t^{1-1/\varepsilon} X^{1/\varepsilon}$. With these redefinitions we have

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

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

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

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 chains

$$\sigma_t \in \{\sigma_L, \sigma_H\}, \text{where } \Pr(\sigma_{t+1} = \sigma_j | \sigma_t = \sigma_k) = \pi_{k,j}^{\sigma}. \tag{2}$$

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

Physical capital accumulation is given by

$$K_{t+1} = (1 - \delta)K_t + I_t, \tag{3}$$

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:

$$G_t = c_k S_t \mathbf{1}_{\{I_t \neq 0\}}, \tag{4}$$

in which $c_k > 0$ 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

$$\Pi_t = S_t - \bar{W} L_t - F. \tag{5}$$

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

$$N_{t+1} = (1 + r_n)\, N_t + H_t, \tag{6}$$

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 et al. [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

$$E_t = \Pi_t - I_t - H_t - G_t. \tag{7}$$

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), 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 et al. [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 with poor accounting information.

[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 et al. [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.

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

$$\eta_t \in \{\eta_L, \eta_H\}, \text{where } \Pr\left(\eta_{t+1} = \eta_j | \eta_t = \eta_k\right) = \pi^{\eta}_{k,j}. \tag{8}$$

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 as in Gomes [2001]. The external equity costs Ψ_t are assumed to scale with firm size as measured by the revenue:

$$\Psi_t = \phi\left(\eta_t, \sigma_t\right) S_t \mathbf{1}_{\{E_t<0\}}. \tag{9}$$

Finally, firms do not incur costs when paying dividends or repurchasing shares. Note that $\phi\left(\eta_t, \sigma_t\right)$ 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 costs of external financing are associated with heightened uncertainty. For example, the aggregate Baa-Aaa spread on corporate bonds has a correlation with the VIX at around 0.65. 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 when $\sigma_t = \sigma_L$, to capture the positive correlation between financing cost and uncertainty in the data.

2.4 Firm's problem

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

$$V_t = \max_{I_t, L_t, K_{t+1}, N_{t+1}} \left[E_t - \Psi_t + \beta \mathbb{E}_t V_{t+1}\right], \tag{10}$$

subject to firms' capital accumulation equation (Eq. 3) and cash accumulation equation (Eq. 6), 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 and firms' real activity and financial flows.

3.1 Calibration

The model is solved at a quarterly frequency. Table 3 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. We then simulate 100 artificial samples and report the cross-sample average results as model moments.

[Insert Table 3 here]

Firm's technology and uncertainty parameters. We set the share of capital 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, close 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 $r_n = 0.8 r_f$ 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 output (calibrated as the 20% of the median output on the output 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 et al. [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 $\lambda = 3\%$ so that the implied correlation between the external financing cost and the uncertainty is 70%, close to the correlation between Baa-Aaa spread and the VIX in the data in our sample. The calibrated financial costs also imply on average 4.25% of the sales, consistent with 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 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.

[11] We have also solved the model with $\eta_H/\eta_L = \{2, 8, 16, 20\}$ 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.

[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.

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 net payout (defined as positive payout minus the absolute value of equity issuance) on the lagged growth of volatility ($\Delta\sigma_{t-1}$) 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.

Table 4 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 investment while cash holdings rises.[14] Row (B) 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 (C) we turn to the classic real frictions only model and see that the impact of uncertainty on investment and employment growth falls from -0.077 to -0.042 and -0.027 to -0.014 respectively. This implies a finance-uncertainty-multiplier of 1.83 (=0.077/0.042) for investment and 1.95 (=0.027/0.014) for employment. So introducing financial frictions to the classic uncertainty model roughly doubles the impact of uncertainty shocks.

[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 results (Row A) and benchmark results (Row B) have similar quantitative magnitudes noting we did not calibrate our parameters to meet these moments.

In Row (D) 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 financial (dividend and cash impacts). 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 (without financial costs cash is zero), and large dividend impacts due to extreme fluctuations in equity payouts.

[Insert Table 4 here]

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 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 in quarter zero kick uncertainty and/or financing costs up to its high level in period 0 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 1.3% 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 and attrition continues to erode capital and labor 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 plants, which with reduced investment and hiring leads to more input mis-allocation.

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 2.4%, 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 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 1.3% 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 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 (8) - 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 0.8% 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. Finally, in the benchmark model (red line, triangle symbols) we see by far the largest impact, 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). 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.[16] Hence, even for financial shocks there is a multiplier effect or about 2 between real and financial frictions.

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). But collectively their impact is significantly larger - for example, the drop in output from an uncertainty or financial shock alone is 2.4% and 2.3% respectively, while jointly they lead to an output fall of 4%. 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.

[16] This financial shock leads to about 1/4 of the drop in aggregate TFP of an uncertainty shock model because with financial shocks only investment and hiring slows, while with uncertainty TFP also becomes more volatile (so in the cross-section the correlation between K and L with A drops much faster).

3.4.2 Robustness

In this section we consider - changes in parameter values, general equilibrium and debt financing. These are plotted in Figure 6 and 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 $\pi^{\sigma}_{L,H} = 0.05$ and $\pi^{\sigma}_{H,H} = 0.5$, 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 shock is now less persistent.

General equilibrium Currently the model is in a particular 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 et al. [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 shocks. In particular, we allow interest rates to 1% lower during periods of high uncertainty. So far we find broad robustness of our results on the impact of uncertainty shocks with a similar sized drop but somewhat faster rebound (light-blue line with triangles in Figure 6).

Debt financing In the model we examine equity financing and ignored debt to reduce the state space of the model. We can also simulate a model with both debt and equity financing, and as we show in this section the results are broadly similar. Our intuition was that when debt is collateral constrained, both margins of debt and equity financing are costly for firms, hence frictions on debt and equity altogether amplify the impact of uncertainty shocks.

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

$$B_{t+1} \leq \varphi K_t. \tag{11}$$

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

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

$$E_t = (1-\tau)\,\Pi_t + \tau\delta K_t + \tau r_f B_t - I_t - H_t - G_t + B_{t+1} - (1+r_f)B_t, \tag{12}$$

in which τ is the corporate tax rate, $\tau\delta K_t$ is the depreciation tax shield, $\tau r_f B_t$ is the interest tax shield. The external equity financing cost remains the same as in the benchmark model. We set the liquidation value $\varphi = 0.85$ following Hennessy and Whited [2005] and the tax rate $\tau = 0.2$ following Gomes and Schmid (2010). Note that in the model debt derives value from substituting costly equity financing while not from the standard tax shield benefit in the finance literature. We see in Figure 6 a somewhat smaller initial drop as firms can substitute debt for equity financing (green line, + symbols), but a slightly more persistent impact of because of debt hangover.

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 above 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.

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).[17] 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

[17] 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).

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 $I_{i,t} = \frac{CAPEX_{i,t}}{K_{i,t-1}}$ where K is net property plant and equipment, and $CAPEX$ is capital expenditures. The changes and ratios of real and financial variables are then all 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 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

$$r_{i,t}^{risk\_adj} = \alpha_j + \sum_c \beta_j^c \cdot r_t^c + \epsilon_{i,t} \tag{13}$$

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 SIC 3-digit level to reduce the role of idiosyncratic noise in firm-level returns, and thus increase precision in estimating our main coefficients of interest, β_j^c. 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. For policy uncertainty since we do not have a time-varying first-moment for this our exposure measure is the industry federal contract share from Baker et al. (2016).

The risk-adjusted returns in 13 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 13 we define firm daily risk-adjusted returns as the residuals of regressing firms' excess return on the daily Carhart factors:

$$r_{i,t}^{excess} = \alpha_i + \beta_{i,mkt} \cdot MKT_t + \beta_{i,HML} \cdot HML_t + \beta_{i,SMB} \cdot SMB_t + \beta_{i,UMD} \cdot UMD_t + \varepsilon_{i,t} \tag{14}$$

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 13) 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 13 and 14 and raw or risk adjusted returns.

The daily independent variables in 13 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 [18], the return on the US 10-year treasury note [19], and the growth in economic policy uncertainty from Baker et al. [2016]. For these 10 aggregate market price shocks (oil, 7 currencies, treasuries, and policy) we need not only their daily returns (for calculating the sensitivities β_j^c in equation 13) 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 et al. [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 13 for their

[18] 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.

[19] 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.

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, $\omega_j^c = \frac{abs(t_j^c)}{\sum\limits^{c} abs(t_j^c)}$. Thus, we adjust the sensitivities within each industry by their statistical power in 13. 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 13 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 uncertainty 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.

In terms of timing, in the first stage when we regress annual firm-level uncertainty $\Delta\sigma_{i,t}$ shocks on the 10 composite exposure terms $\mid \beta_j^{c,weighted} \mid \cdot\Delta\sigma_t^c$, aggregate uncertainty shocks $\Delta\sigma_t^c$ are contemporaneous growths but the exposures $\beta_j^{c,weighted}$ are always estimated using information prior to the uncertainty growth, in particular with a lag of 24 months. For example, for a firm with a fiscal-year end in December 2012, the exposures are estimated using 13 and a window of 10-years of daily data ending with information up to December of 2010 (i.e., lag of 24 months), and the growth $\Delta\sigma_t^c$ is the change in the annual option-implied uncertainty measured over the course of 2011 to that of 2012.

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 $\beta_j^{c,weighted} \cdot r_t^c$.[20] 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), yet our focus is on the effects of the instrumented firm-level uncertainty shocks, $\widehat{\Delta\sigma_{i,t}}$

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 5 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 19.89) on return volatility, showing that firms tend to invest more when 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.[21]

[20] 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.

[21] We reestimate both specifications in columns (1) and (4) on a common sample of 17,487 observations in table (A4) and find the realized and implied volatility coefficients are -0.033 and -0.079, suggesting the three fold difference arises from the difference in variables rather than samples (e.g. realized volatility shocks have a standard deviation

One obvious concern with these OLS regressions is endogeneity - for example, changes in firms' investment plans could change stock-prices. Using lagged uncertainty will help to address this to some extent, but given stock prices are forward looking this is unlikely to fully address the concerns. So we try to address these endogeneity concerns with our instrumentation strategy. In particular, columns 2 and 3 instrument lagged *realized* volatility using the full set of 10 instruments while columns 5 and 6 instrument lagged *implied* volatility. Columns 2 and 5 are univariate while 3 and 6 are multivariate with a full set of controls. In all cases we see 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 A1) would reduce investment by between 4% to 6% (using the results from our preferred multivariate specifications in column (3) and (6)). 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 about 2% or 6% during recessions as show in Figure 1.

[Insert Table 5 here]

5.1.1 First stage results

The first stage instrumental investment results are shown in table 6. Columns (1) and (2) report the first stages for the univariate IV columns (2) and (4) from table 5. We see that the F-

of 0.3 vs 0.2 for implied volatility shocks).

statistics indicate a well identified first stage with values of 166.8 and 78.79 for the Cragg-Donald (CD) F-Statistics (robust standard-errors), and 19.33 and 13.20 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 0.246 and 0.680. 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 positively and mostly significant in the first stage.

We repeat the above examination but adding our full set of controls, columns (3) and (4) present the first stage for the multivariate IV regressions of columns (3) and (6) from table 5. Even when we add our full set of controls we see a well satisfied relevance condition, with CD and KP F-stats of 179.2, 60.41 18.02 and 11.49 respectively, and non-rejected Sargan-Hansen validity test p-values of 0.873 and 0.988. Moreover, each instrument remains individually positively correlated with uncertainty shocks.

[Inset Table 6 here]

5.2 Intangible capital, Employment, and sales

Table 7 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 5. 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 F-statistics above 10 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.

[Insert Table 7 here]

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 8 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, 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.

[Insert Table 8 here]

5.4 Instrument and credit supply robustness

In Appendix Table A2 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 42,732)[22]. 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 13.34 to 20.35 in all specifications (the CD F–test is always above 100), and the Hansen over-identifying test does not reject in any specification with p-values of 0.8 or above. Although in column (10) cost of goods sold does not respond to uncertainty shocks, all other real and financial firm-outcomes 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.

[Insert Table A2 here]

In Appendix table A3 we investigate the robustness of the results to including additional firm-level controls for financial constraints. One concern could be that uncertainty reduces financial supply - for example, banks are unwilling to lend in periods of high uncertainty - which causes the results we observe. To 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

[22] 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.

combined in columns 5 and 5A. In summary, as we can see from Table A3 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 suggests that financial supply conditions are unlikely to be the main driver of our results.

[Insert Table A3 here]

Finally, in Table A4 we re-examine our main investment Table 5 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 17,487 observations across all columns. Compared to the main Table 5 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.

[Insert Table A4 here]

5.5 The finance uncertainty multiplier

Finally, Table 9 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 9 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:

$$\begin{gathered} I_{i,t}/K_{i,t-1} = \beta_0 + \beta_1 \Delta\sigma_{i,t-1} + \beta_2 D_{crisis\_year,t} \\ + \beta_3 D_{crisis\_year,t} \cdot \Delta\sigma_{i,t-1} + \beta_4 D_{fin.constrained,i,t-1} + \beta_5 D_{fin.constrained,i,t-1} \cdot \Delta\sigma_{i,t-1} \\ + \beta_6 D_{crisis\_year,t} \cdot D_{fin.constrained,i,t-1} + \beta_7 D_{crisis\_year,t} \cdot D_{fin.constrained,i,t-1} \cdot \Delta\sigma_{i,t-1} \end{gathered} \tag{15}$$

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. Employing dummies to classify firms into groups rather than using firm-level financing constraint measures in our interaction terms facilitates the comparison of key coefficients β_3, β_7 across different noisy estimates of financing constraints.[23]

Column (1) presents our baseline 2SLS multivariate specification with full set of controls presented in Table 5 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 fully attributable to the period of large uncertainty spikes and large rises in financing frictions seen in the core crisis years of the great recession, as seen by the highly significant interaction term $D_{crisis\_year,t} \cdot \Delta\sigma_{i,t-1}$ which subsumes the effect of the uncertainty shock alone. This is consistent with the main thesis in this paper that financial constraints substantially amplify the impact of uncertainty shocks.

[Insert Table 9 here]

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 15 , 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

[23] 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.

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.[24] We do this in all but the S&P credit-rating financial constraint measure, column (3). Here we follow Duchin et al. [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).[25]

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 [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 9 provides important empirical evidence in support of the testable predictions of the model of section 2 for an interactive

[24] 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.

[25] 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).

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 et al. [2010]). Volatility is the annual realized stock return volatility. 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 A5 repeats the examination done in Table 9, but using option-implied firm-level uncertainty shocks instead of realized uncertainty shocks. The inferences on the economic importance of uncertainty shocks are robust to these forward-looking uncertainty data.

[Insert Table A5 here]

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.

Taken together, 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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A Numerical algorithm appendix

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 appendix

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 et al. [2016]. Table 2 presents descriptive statistics of main variables used in the firm-level panel regressions. Our annual sample period begins in 1963 and ends in 2016.[26]

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 above 9000.[27] When Compustat reports more than one annual data for the same-company in a given fiscal year (e.g., when a company

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

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

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.

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 $I_{i,t} = \frac{CAPEX_{i,t}}{K_{i,t-1}}$ where K is net property plant and equipment, and $CAPEX$ 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 et al. [2010], $Q_{i,t} = (market\ value\ of\ assets)\ /(0.9 *\ book\ assets + 0.1 *\ market\ value\ of\ assets)$, where market value of assets is ($AT + ME + CEQ - TXDB$), ME is CRSP market value of equity (i.e. stock price times shares outstanding), book assets is AT, and $TXDB$ is deferred taxes. We handle outliers in Tobin's Q by bounding Q above at 10. Return on assets, $ROA_t = EBIT/AT$, where $EBIT$ is earnings before interest and tax. We further control for firm size, defined as log $SALE$.

As for our main variable of interest firm-level uncertainty shocks, $\Delta\sigma_{i,t}$, we measure uncertainty in two ways, realized and option-implied uncertainty. Realized uncertainty is the annual volatility of the firm's realized CRSP stock return. 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. Given an option price, duration, and strike price, along with interest rates, underlying stock price, and dividends, the Black-Scholes formula is used to back out implied volatility. This is an annualized measure representing the standard deviation of the expected change in the stock price. Note that this is not a directional measure, but rather an expectation of absolute stock price movements regardless of their direction.

One of the advantages of using implied volatilities is that they can be measured across a variety of time horizons using options with different expiration dates. In particular, OptionMetrics calculates implied volatilities for durations ranging from 30 to 730 days. We can use these implied volatility horizons to measure uncertainty over different forward-looking periods, yet to be consistent with the annual Compustat data used throughout, our main tests focus only on 365-day implied volatility. However, our main results are largely similar if we employ 91-day implied volatility.

While implied volatility data is available for a variety of strike prices, we restrict our analysis to at-the-money-forward options; i.e., options for which the strike price is equal to the forward price of the underlying stock at the given expiration date. The forward (or expected future) price is calculated from the current stock price, the stock's dividend payout rate, and the interest rate yield curve. 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[28].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 13 .

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.

[28] 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 $j's$ 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 $\Delta\sigma_{j,t-1} = (\sigma_{j,t-1} - \sigma_{j,t-2})/(\frac{1}{2}\sigma_{j,t-1} + \frac{1}{2}\sigma_{j,t-2})$ 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 2
Descriptive Statistics

Variables in 2SLS	Obs.	Mean	S. Dev	P1	P10	P50	P90	P99
Dependent								
Investment Rate	128,766	0.247	0.152	0.011	0.0658	0.214	0.500	0.500
ΔEmployment	126,158	0.026	0.236	-0.782	-0.194	0.021	0.258	0.763
ΔIntangible Cap. Invest.	67,795	0.077	0.201	-0.544	-0.138	0.077	0.294	0.653
ΔCost of Goods Sold	130,359	0.079	0.294	-1.015	-0.179	0.079	0.344	1.046
ΔDebt Total	129,300	0.046	0.672	-2	-0.518	0	0.741	2
ΔPayout	130,561	0.062	0.918	-2	-1.188	0	1.467	2
ΔCash Holdings	130,373	0.042	0.705	-1.745	-0.844	0.042	0.936	1.808
Independent								
ΔRealized Volatility	130,561	-0.000	0.304	-0.682	-0.376	-0.012	0.387	0.791
ΔImplied Volatility	27,013	-0.015	0.200	-0.435	-0.259	-0.026	0.247	0.513
Book Leverage	128,810	0.322	0.282	0	0	0.291	0.673	1.268
Stock Return	130,561	0.177	0.692	-0.770	-0.460	0.066	0.852	2.778
Log Sales	130,008	5.051	2.158	-0.409	2.403	5.003	7.859	9.967
Return on Assets	130,518	0.046	0.188	-0.819	-0.113	0.081	0.194	0.326
Tangibility	130,140	0.550	0.366	0.034	0.138	0.479	1.058	1.648
Tobin's Q	129,168	1.486	0.844	0.567	0.790	1.215	2.551	4.777
Instruments								
ΔVol Exposure Cad	44,761	3e-04	0.006	-0.015	-0.001	0	0.001	0.019
ΔVol Exposure Euro	44,302	-2e-04	0.011	-0.031	-0.004	0	0.001	0.043
ΔVol Exposure Jpy	51,313	2e-04	0.005	-0.011	-0.001	0	6e-05	0.015
ΔVol Exposure Aud	51,313	2e-05	0.006	-0.018	-0.003	0	0.003	0.022
ΔVol Exposure Sek	44,761	2e-04	0.007	-0.021	-0.004	0	0.002	0.032
ΔVol Exposure Chf	51,313	1e-04	0.009	-0.021	-0.003	0	0.001	0.029
ΔVol Exposure Gbp	51,313	1e-04	0.005	-0.013	-6e-04	0	0	0.019
ΔVol Exposure Oil	29,286	3e-05	0.011	-0.042	-0.001	0	0.001	0.029
ΔVol Exposure Policy	51,313	3e-07	2e-05	-8e-05	0	0	0	8e-05
ΔVol Expos.Treasury	29,466	-0.652	8.655	-33.33	-4.658	0	2.358	27.57

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 et al. [2016]. See sections 4 and 5 for the details on the construction of variables.

Table 3
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 = 075
Wage	$\bar{w}$	1	Wage rate normalized to 1
Rate of depreciation for capital	δ	0.03	Capital depreciation rate assumed 3% per month
Fixed cost of investment	c_k	0.01	1% of quarterly output (We also show robustness with 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 financing cost .5% of output (Altinkilic and Hansen 2000)
High external financing cost state	η_H	0.05	High financing cost 5% of output (Altinkilic & Hansen 2000). Also tried 0.025 & 0.1
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	0.03	Correlation between the Baa-Aaa spread and VIX

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

Table 4
Coefficient on changes in volatility for real and financial variables.

	Real		Financial	
	I/K	dEmp	dCash	dDiv
A: Data				
ΔVolatility	-0.080	-0.068	0.197	-0.522
B: Real frictions				
ΔVolatility	-0.042	-0.014	0.000	-0.031
C: Financial frictions				
ΔVolatility	-0.021	-0.004	1.071	-0.700
D: Real+financial frictions				
ΔVolatility	-0.077	-0.027	0.316	-0.372
E: No frictions				
ΔVolatility	0.003	0.006	0.000	-7.230

Row (A) Data reports the results for investment rate, employment growth, cash growth and equity payout growth from columns (2) of tables (5), (7) and (8) respectively. Rows (B) to (E) reports the model counterparts from regressions using simulation data on lagged volatility ($\sigma^2_{i,t}$). The reported statistics in the model are averages from 100 samples of simulated data, each with 3000 firms and 200 quarterly observations. We report the cross-simulation averaged annual moments. I/K is the investment rate, dEmp is the employment growth, dCash is the cash growth rate, and dDiv the dividend growth in the model and cash dividend plus repurchase growth in the data. For comparability all the regressions (in the data and model) include firm and time fixed effects and all are significant at the 1% level with firm-clustered standard errors. The only difference is employment is annual in the real data (since no quarterly real employment data is available).

Table 5
Investment rate

Investment rate$_{i,t}$	(1) OLS Realized	(2) IV Realized	(3) IV Realized	(4) OLS Implied	(5) IV Implied	(6) IV Implied
ΔVolatility$_{i,t-1}$	-0.031***	-0.080***	-0.028***	-0.089***	-0.215***	-0.079**
	(-19.896)	(-3.881)	(-2.754)	(-10.520)	(-4.220)	(-2.584)
Book Leverage$_{i,t-1}$			-0.050***			-0.037***
			(-8.444)			(-5.739)
Stock Return$_{i,t-1}$			0.008***			0.005*
			(2.957)			(1.747)
Log Sales$_{i,t-1}$			-0.021***			-0.020***
			(-6.673)			(-5.013)
Return on Assets$_{i,t-1}$			0.129***			0.120***
			(5.188)			(3.710)
Tangibility$_{i,t-1}$			-0.114***			-0.120***
			(-5.953)			(-3.366)
Tobin's Q$_{i,t-1}$			0.050***			0.054***
			(10.013)			(8.330)
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	127,361	28,650	28,326	26,237	17,683	17,487
F 1st st. Cragg-D		166.8	179.2		78.79	60.41
F 1st st. Kleib.-P		19.33	18.02		13.20	11.49
p-val Sargan–H J		0.246	0.873		0.680	0.988

This 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} (capex/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 instruments 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 lagged exposure to changes in economic policy uncertainty from Baker et al. [2016]. We measure firm-level uncertainty in two ways: realized and implied volatility. Annual realized volatility is the 12-month standard deviation of daily stock returns from CRSP. We annualize this standard deviation by multiplying by the square root of 252 (average trading days in a year). Implied volatility is proxied by the annual average of each firm's daily 365-day implied volatility of at-the-money-forward call options from OptionMetrics. All regressors are lagged by 1-year. To ensure that the changes in both firm- and aggregate-level volatility are annual we require a 12 month distance between each firm's fiscal-year end dates, starting from $t-2$ and ending in t. In all specifications we include both firm and calendar-year fixed effects. Standard errors are clustered at the 3-digit SIC industry. Our main set of firm-level controls include the lagged level of book leverage, stock return, log sales, return on assets, tangibility, and Tobin's Q. Moreover, 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 sections 4 and 5 for details on data.

Table 6
Investment rate - 2SLS 1st Stage Results

Specification:	Univariate		Multivariate	
Set-up: ΔVolatility$_{i,t-1}$	Realized	Implied	Realized	Implied
ΔVol Exposure Cad$_{i,t-1}$	3.975***	1.516***	3.700***	1.304***
	(5.07)	(3.8)	(4.93)	(3.39)
ΔVol Exposure Euro$_{i,t-1}$	1.259***	0.611***	1.154***	0.458***
	(4.22)	(3.69)	(4.05)	(2.94)
ΔVol Exposure Jpy$_{i,t-1}$	2.368***	0.364	2.375***	0.393
	(3.98)	(0.84)	(4.01)	(0.94)
ΔVol Exposure Aud$_{i,t-1}$	5.152***	1.736***	5.323***	1.724***
	(7.74)	(5.85)	(9.02)	(5.94)
ΔVol Exposure Sek$_{i,t-1}$	4.308***	1.320***	4.848***	1.557***
	(7.72)	(3.84)	(7.57)	(4.26)
ΔVol Exposure Chf$_{i,t-1}$	2.120***	1.255***	2.403***	1.353***
	(6.14)	(6.07)	(6.3)	(5.7)
ΔVol Exposure Gbp$_{i,t-1}$	3.036***	1.826***	2.814***	1.667***
	(5.35)	(4.33)	(5.35)	(4.65)
ΔVol Exposure Policy$_{i,t-1}$	551.441***	222.584*	561.499***	172.483†
	(3.12)	(1.93)	(3.3)	(1.64)
ΔVol Expos.Treasury$_{i,t-1}$‡	3.079***	1.099***	3.036***	0.933***
	(8.52)	(4.56)	(8.57)	(4.63)
ΔVol Exposure Oil$_{i,t-1}$	3.044***	1.846***	4.307***	1.684***
	(9.06)	(7.71)	(5.07)	(5.1)
Observations	28,650	17,683	28,326	17,487
F-test 1st stage Cragg-Donald	166.8	78.79	179.2	60.41
F-test 1st stage Kleibergen-Paap	19.33	13.20	18.02	11.49
p-value Hansen-Sargan J	0.246	0.680	0.873	0.988

This 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 5, 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 instruments 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 lagged exposure to changes in economic policy uncertainty from Baker et al. [2016]. We measure firm-level uncertainty in two ways: realized and implied volatility. Annual realized volatility is the 12-month standard deviation of daily stock returns from CRSP. We annualize this standard deviation by multiplying by the square root of 252 (average trading days in a year). Implied volatility is proxied by the annual average of each firm's daily 365-day implied volatility of at-the-money-forward call options from OptionMetrics. All regressors are lagged by 1-year. To ensure that the changes in both firm- and aggregate-level volatility are annual we require a 12 month distance between each firm's fiscal-year end dates, starting from $t-2$ and ending in t. In all specifications we include both firm and calendar-year fixed effects. Standard errors are clustered at the 3-digit SIC industry. Our main set of firm-level controls include the lagged level of book leverage, stock return, log sales, return on assets, tangibility, and Tobin's Q. Moreover, 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 sections 4 and 5 for details on data.

Table 7
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**	-0.138***	-0.187***	-0.056
	(-10.848)	(-4.134)	(-2.208)	(-9.347)	(-2.869)	(-1.066)
Observations	66,865	17,168	17,013	16,290	10,982	10,887
F 1st st. Cragg-D		109.6	111.9		41.06	38.04
F 1st st. Kleib.-P		15.10	16.33		8.325	10.30
p-val Sargan–H J		0.329	0.416		0.241	0.302
B: ΔEmployment$_{i,t}$						
ΔVolatility$_{i,t-1}$	-0.037***	-0.068***	-0.007	-0.115***	-0.241***	-0.045
	(-11.867)	(-2.657)	(-0.248)	(-10.677)	(-3.429)	(-0.550)
Observations	124,768	28,495	28,158	26,132	17,591	17,396
F 1st st. Cragg-D		165.9	178.1		79.12	60.25
F 1st st. Kleib.-P		18.92	17.59		13.36	11.66
p-val Sargan–H J		0.177	0.586		0.231	0.440
C: ΔCost of Goods Sold$_{i,t}$						
ΔVolatility$_{i,t-1}$	-0.056***	-0.251**	-0.137***	-0.209***	-0.807**	-0.337***
	(-10.376)	(-2.241)	(-3.642)	(-5.642)	(-2.436)	(-3.086)
Observations	128,974	28,720	28,376	26,384	17,710	17,507
F 1st st. Cragg-D		167.6	179.8		78.98	60.42
F 1st st. Kleib.-P		19.24	17.94		13.18	11.50
p-val Sargan–H J		0.170	0.029		0.181	0.023

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 5. 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. The latter instrument lagged changes in firm-level volatility with industry-level (3SIC) exposure to 10 aggregate lagged uncertainty shocks. These instruments 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 lagged exposure to changes in economic policy uncertainty from Baker et al. [2016]. We measure firm-level uncertainty in two ways: realized and implied volatility. Annual realized volatility is the 12-month standard deviation of daily stock returns from CRSP. We annualize this standard deviation by multiplying by the square root of 252 (average trading days in a year). Implied volatility is proxied by the annual average of each firm's daily 365-day implied volatility of at-the-money-forward call options from OptionMetrics. All regressors are lagged by 1-year. To ensure that the changes in both firm- and aggregate-level volatility are annual we require a 12 month distance between each firm's fiscal-year end dates, starting from $t-2$ and ending in t. In all specifications we include both firm and calendar-year fixed effects. Standard errors are clustered at the 3-digit SIC industry. Our main set of firm-level controls include the lagged level of book leverage, stock return, log sales, return on assets, tangibility, and Tobin's Q. Moreover, 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 sections 4 and 5 for details on data.

Table 8
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$_{i,t-1}$	-0.078***	-0.256***	-0.160**	-0.198***	-0.811***	-0.678***
	(-9.702)	(-3.400)	(-2.382)	(-6.744)	(-5.407)	(-4.217)
Observations	127,911	28,545	28,320	26,198	17,586	17,470
F 1st st. Cragg-D		166.3	179.5		77.67	60.15
F 1st st. Kleib.-P		19.10	17.85		13.14	11.52
p-val Sargan–H J		0.0967	0.334		0.761	0.856
B: ΔPayout$_{i,t}$						
ΔVolatility$_{i,t-1}$	-0.158***	-0.522***	-0.297***	-0.521***	-1.394***	-0.803**
	(-13.318)	(-4.772)	(-2.710)	(-8.548)	(-4.743)	(-2.590)
Observations	129,158	28,738	28,389	26,402	17,715	17,512
F 1st st. Cragg-D		167.6	180		78.97	60.41
F 1st st. Kleib.-P		19.24	17.93		13.17	11.48
p-val Sargan–H J		0.370	0.687		0.988	0.996
C: ΔCash holding$_{i,t}$						
ΔVolatility$_{i,t-1}$	0.032***	0.197***	0.148**	0.115***	0.639***	0.516**
	(3.714)	(2.984)	(2.253)	(3.573)	(3.850)	(2.435)
Observations	128,985	28,721	28,374	26,381	17,709	17,506
F 1st st. Cragg-D		167.6	179.8		78.92	60.38
F 1st st. Kleib.-P		19.25	17.93		13.17	11.50
p-val Sargan–H J		0.664	0.559		0.441	0.511

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 5. 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. The latter instrument lagged changes in firm-level volatility with industry-level (3SIC) exposure to 10 aggregate lagged uncertainty shocks. These instruments 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 lagged exposure to changes in economic policy uncertainty from Baker et al. [2016]. We measure firm-level uncertainty in two ways: realized and implied volatility. Annual realized volatility is the 12-month standard deviation of daily stock returns from CRSP. We annualize this standard deviation by multiplying by the square root of 252 (average trading days in a year). Implied volatility is proxied by the annual average of each firm's daily 365-day implied volatility of at-the-money-forward call options from OptionMetrics. All regressors are lagged by 1-year. To ensure that the changes in both firm- and aggregate-level volatility are annual we require a 12 month distance between each firm's fiscal-year end dates, starting from $t-2$ and ending in t. In all specifications we include both firm and calendar-year fixed effects. Standard errors are clustered at the 3-digit SIC industry. Our main set of firm-level controls include the lagged level of book leverage, stock return, log sales, return on assets, tangibility, and Tobin's Q. Moreover, 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 sections 4 and 5 for details on data.

Table 9
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)	-0.028***	-0.012	-0.010	-0.025**	-0.026**	-0.022**	-0.021**	-0.017†
$D_{crisis,t}$		-	-	-	-	-	-	-
$D_{crisis,t} \cdot \Delta$Volatility$_{i,t-1}$		-0.087***	-0.070***	-0.063***	-0.068***	-0.102***	-0.059**	-0.092***
$D_{fin\_constrained,i,t-1}$			-0.006*	0.006	0.005	0.002	-	-0.026
$D_{fin_constrained,i,t-1} \cdot \Delta$Volatility$_{i,t-1}$			-0.007	0.020†	0.019	0.017	0.006	0.016
$D_{crisis,t} \cdot D_{fin\_constrained,i,t-1}$			0.003	-0.012*	-0.012*	-0.018***	-0.000	-0.013**
$D_{crisis,t} \cdot D_{fin_constrained,i,t-1} \cdot \Delta$Volatility$_{i,t-1}$			-0.028	-0.047**	-0.053**	-0.039*	-0.021	-0.042*
Observations	28,326	28,326	28,326	21,345	21,203	21,315	22,380	21,353
F-test 1st stage Cragg-D	179.2	80.92	39.33	26.97	33.28	22.34	33.34	25.18
F-test 1st stage Kleib.-P.	18.02	8.550	5.495	4.249	4.793	5.224	4.745	5.810
p-val Sargan–Hansen J	0.873	0.652	0.587	0.530	0.728	0.805	0.944	0.671

This 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} (capex/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 5. Column 1 restates the benchmark regression (3) in Table 5. 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 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. Columns 3 to 8 run a difference-in-difference-in-difference specification where we 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 et al. [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 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 [2010]. We thank Toni Whited for suggesting this last index. In all specifications we include both firm and calendar-year fixed effects. Standard errors are clustered at the 3 digit SIC industry. Our main set of firm-level controls include the lagged level of book leverage, stock return, log sales, return on assets, tangibility, and Tobin's Q. Moreover, 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 sections 4 and 5 for details on data.

Table A1
Coefficient on changes in volatility for real and financial variables.

High financial state/low financial sate	**Real**		**Financial**	
	I/K	dEmp	dCash	dDiv
A: Benchmark				
ΔVolatility	-0.077	-0.027	0.316	-0.372
B: H/L = 5				
ΔVolatility	-0.085	-0.029	0.263	-0.322
C: Different transition matrix of η_t				
ΔVolatility	-0.079	-0.027	0.245	-0.399
D: Model with debt and equity				
ΔVolatility	-0.078	-0.028	0.141	-0.511

This table reports the model regression results of real and financial variables on volatility growth. The reported statistics in the model are averages from 100 samples of simulated data, each with 3000 firms and 200 quarterly observations. We report the cross-simulation averaged annual moments. I/K is the investment rate, dEmp is the employment growth, dCash is the cash growth rate, and dDiv the dividend growth in the model and cash dividend plus repurchase growth in the data. Panel A is the benchmark calibration with this ratio equal to 10. 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 E sets the transition probabilities of financial shocks of $\pi^{\sigma}_{L,H} = 0.05$ and $\pi^{\sigma}_{H,H} = 0.5$. Panel D extends the benchmark by including collateralized debt. 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
2SLS Sensitivity to Individual Instruments

IV Dropped	(1) None	(2) Cad	(3) Euro	(4) Jpy	(5) Aud	(6) Sek	(7) Chf	(8) Gbp	(9) Policy	(10) Oil+Treasuries
Real Variables										
Investment Rate$_{i,t}$	-0.028***	-0.031***	-0.026**	-0.028***	-0.031***	-0.031**	-0.028**	-0.027**	-0.028***	-0.033**
ΔIntang. Cap. Invest.$_{i,t}$	-0.036**	-0.036**	-0.035*	-0.039**	-0.038**	-0.031*	-0.042**	-0.041**	-0.034**	-0.039*
ΔEmployment$_{i,t}$	-0.007	-0.004	-0.004	-0.007	-0.005	-0.031	-0.013	-0.007	-0.006	0.011
Financial Variables										
ΔDebt Total$_{i,t}$	-0.160**	-0.154**	-0.145**	-0.160**	-0.198***	-0.196***	-0.158**	-0.157**	-0.163**	-0.196**
ΔPayout$_{i,t}$	-0.297***	-0.320***	-0.286***	-0.293***	-0.364***	-0.279**	-0.254**	-0.288**	-0.289***	-0.444***
ΔCash Holdings$_{i,t}$	0.148**	0.141**	0.148**	0.144**	0.182**	0.151*	0.103†	0.140**	0.143**	0.254**
1st moment 10IV$_{i,t-1}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm, time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE cluster (3SIC)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Investment Rate Stats										
Observations	28,326	28,326	28,326	28,326	28,326	28,326	28,326	28,326	28,326	42,732
F 1st stage Cragg-D	179.2	185.2	191.4	195.6	169.2	158.5	179.9	190.3	193.9	105.2
F 1st stage Kleib.-P.	18.02	20.35	20	18.49	14.91	18.71	18.50	16.92	19.05	13.34
p-val Sargan–Hans J	0.873	0.935	0.865	0.813	0.857	0.846	0.806	0.864	0.808	0.972

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 5, 7, and 8. 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. In all specifications we include both firm and calendar-year fixed effects. Standard errors are clustered at the 3 digit SIC industry. Our main set of firm-level controls include the lagged level of book leverage, stock return, log sales, return on assets, tangibility, and Tobin's Q. Moreover, 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 sections 4 and 5 for details on data.

Table A3
2SLS Robustness Tests

Volatility Instrumented	(1) Realized	(2) Realized	(3) Realized	(4) Realized	(5) Realized	(1A) Implied	(2A) Implied	(3A) Implied	(4A) Implied	(5A) Implied
Real Variables										
Investment Rate$_{i,t}$	-0.028***	-0.028***	-0.028***	-0.028***	-0.028***	-0.079**	-0.077***	-0.083**	-0.082***	-0.083***
ΔIntangible Cap. Invest.$_{i,t}$	-0.036**	-0.034**	-0.032**	-0.035**	-0.029*	-0.056	-0.049	-0.057	-0.049	-0.041
ΔEmployment$_{i,t}$	-0.007	-0.006	-0.010	-0.008	-0.008	-0.045	-0.042	-0.048	-0.048	-0.044
Financial Variables										
ΔDebt Total$_{i,t}$	-0.160**	-0.159**	-0.166**	-0.161**	-0.165**	-0.678***	-0.662***	-0.685***	-0.681***	-0.670***
ΔPayout$_{i,t}$	-0.297***	-0.280***	-0.320***	-0.299***	-0.306***	-0.803**	-0.746**	-0.862***	-0.803**	-0.808***
ΔCash Holdings$_{i,t}$	0.148**	0.142**	0.138**	0.148**	0.137**	0.516**	0.514**	0.539***	0.517**	0.541***
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	28,326	28,326	28,148	28,326	28,148	17,487	17,487	17,391	17,487	17,391
F 1st stage Cragg-Donald Wald	179.2	191.5	178	179.1	190.3	60.41	67.22	60	60.99	67.45
F 1st stage Kleibergen-Paap Wald	18.02	20	17.88	18.06	19.84	11.49	13.61	11.83	11.68	13.96
p-val Sargan–Hansen J Chi-sq	0.873	0.873	0.824	0.858	0.806	0.988	0.988	0.970	0.987	0.964

This table presents 2SLS robustness results for all our real and financial outcome variables examined in main Tables 5, 7, and 8. Columns (1) and (1A) restate here the benchmark 2SLS specifications in columns (3) and (6) in each of their main respective Tables. The control covariance w/ market adds each firm's lagged CAPM beta in the full set of controls. The financial constraint index column adds a set of 6 lagged firm-level controls which proxy 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 -where age is the number of years since firm incorporation. 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. The omitted dummy is for no credit ratings. In all specifications we include both firm and calendar-year fixed effects. Standard errors are 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 sections 4 and 5 for the details on the construction of variables and data.

Table A4
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***	-0.081***	-0.029**	-0.079***	-0.216***	-0.079**
	(-4.572)	(-3.531)	(-2.550)	(-7.374)	(-4.174)	(-2.584)
Book Leverage$_{i,t-1}$			-0.040***			-0.037***
			(-6.333)			(-5.739)
Stock Return$_{i,t-1}$			0.006**			0.005*
			(2.156)			(1.747)
Log Sales$_{i,t-1}$			-0.021***			-0.020***
			(-5.100)			(-5.013)
Return on Assets$_{i,t-1}$			0.126***			0.120***
			(3.850)			(3.710)
Tangibility$_{i,t-1}$			-0.124***			-0.120***
			(-3.492)			(-3.366)
Tobin's Q$_{i,t-1}$			0.056***			0.054***
			(8.176)			(8.330)
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	17,487	17,487	17,487	17,487	17,487	17,487
F 1st st. Cragg-D		137.4	145.8		78.34	60.41
F 1st st. Kleib.-P		16.03	15.44		13.16	11.49
p-val Sargan–H J		0.645	0.964		0.699	0.988

This table presents all investment rate regression results shown in main Table 5 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. The 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} (capex/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 instruments 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 lagged exposure to changes in economic policy uncertainty from Baker et al. [2016]. We measure firm-level uncertainty in two ways: realized and implied volatility. Annual realized volatility is the 12-month standard deviation of daily stock returns from CRSP. We annualize this standard deviation by multiplying by the square root of 252 (average trading days in a year). Implied volatility is proxied by the annual average of each firm's daily 365-day implied volatility of at-the-money-forward call options from OptionMetrics. All regressors are lagged by 1-year. To ensure that the changes in both firm- and aggregate-level volatility are annual we require a 12 month distance between each firm's fiscal-year end dates, starting from $t-2$ and ending in t. In all specifications we include both firm and calendar-year fixed effects. Standard errors are clustered at the 3-digit SIC industry. Our main set of firm-level controls include the lagged level of book leverage, stock return, log sales, return on assets, tangibility, and Tobin's Q. Moreover, 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 sections 4 and 5 for details on data.

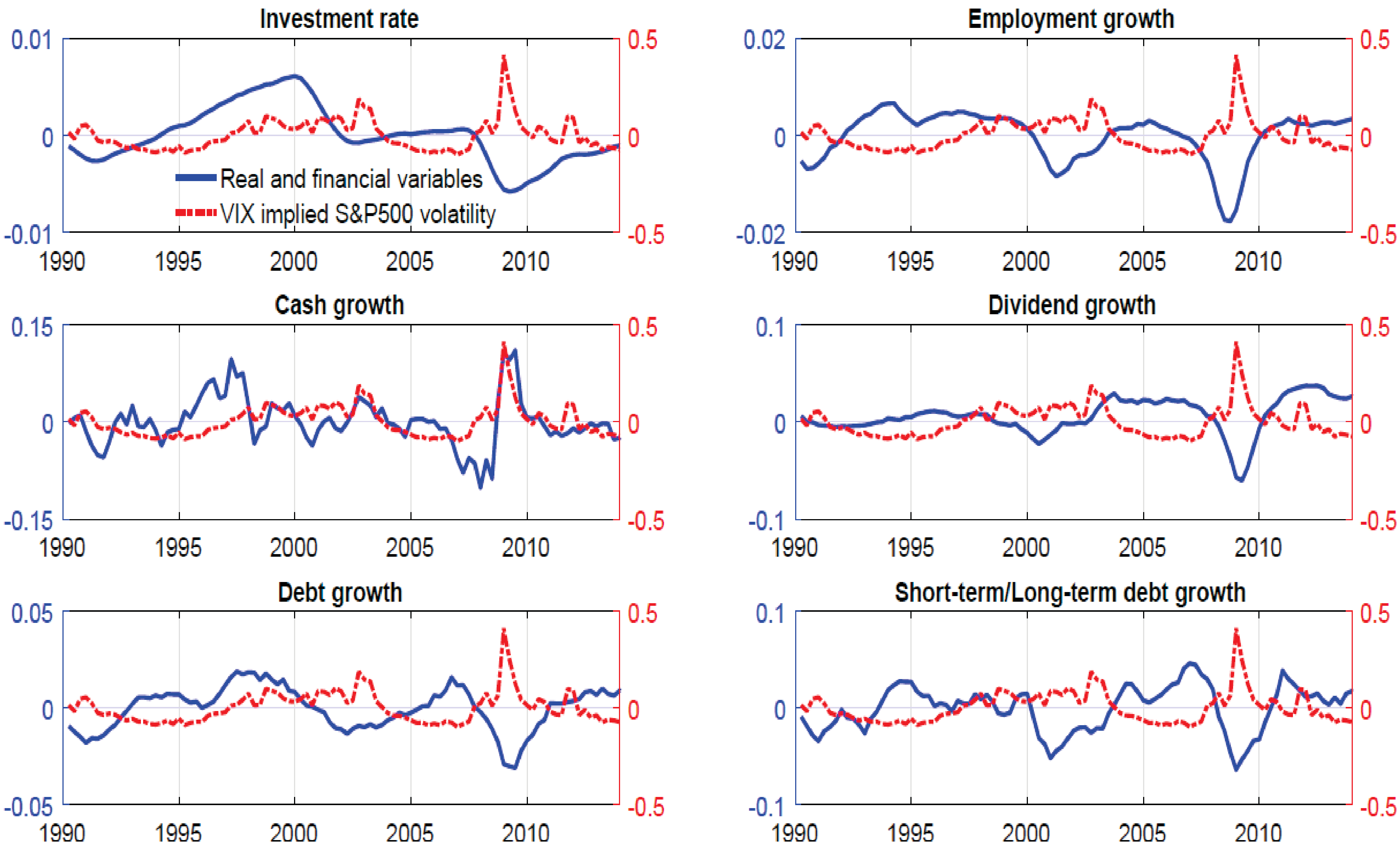
Table A5

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)	-0.079**	-0.045†	-0.032	-0.059**	-0.084***	-0.055**	-0.058*	-0.065**
$D_{crisis,t}$		-	-	-	-	-	-	-
$D_{crisis,t} \cdot \Delta$Volatility$_{i,t-1}$		-0.062***	-0.056**	-0.053**	-0.035	-0.083***	-0.053*	-0.049*
$D_{fin\_constrained,i,t-1}$			-0.006	0.002	0.038*	0.019	-	-0.148***
$D_{fin_constrained,i,t-1} \cdot \Delta$Volatility$_{i,t-1}$			-0.018†	0.048**	0.041†	0.036	0.010	0.039**
$D_{crisis,t} \cdot D_{fin\_constrained,i,t-1}$			0.006	-0.001	-0.007	-0.013	0.000	-0.015*
$D_{crisis,t} \cdot D_{fin_constrained,i,t-1} \cdot \Delta$Volatility$_{i,t-1}$			-0.006	-0.093***	-0.093***	-0.069**	-0.019	-0.065**
Observations	17,487	17,487	17,487	13,084	13,306	13,050	13,943	12,910
F-test 1st stage Cragg-D	60.41	31.99	15.52	15.48	15.52	15.64	13.64	15.45
F-test 1st stage Kleib.-P.	11.49	10.95	8.055	7.678	10.69	6.265	5.141	7.736
p-val Sargan–Hansen J	0.988	0.999	0.998	0.809	0.891	0.565	0.907	0.208

This 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} (capex/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 5. Column 1 restates the benchmark regression (6) in Table 5. Column 2 further adds the interaction of lagged change in implied 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 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. Columns 3 to 8 run a difference-in-difference-in-difference specification where we 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 et al. [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 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 [2010]. We thank Toni Whited for suggesting this last index. In all specifications we include both firm and calendar-year fixed effects. Standard errors are clustered at the 3 digit SIC industry. Our main set of firm-level controls include the lagged level of book leverage, stock return, log sales, return on assets, tangibility, and Tobin's Q. Moreover, 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 sections 4 and 5 for details on data.

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

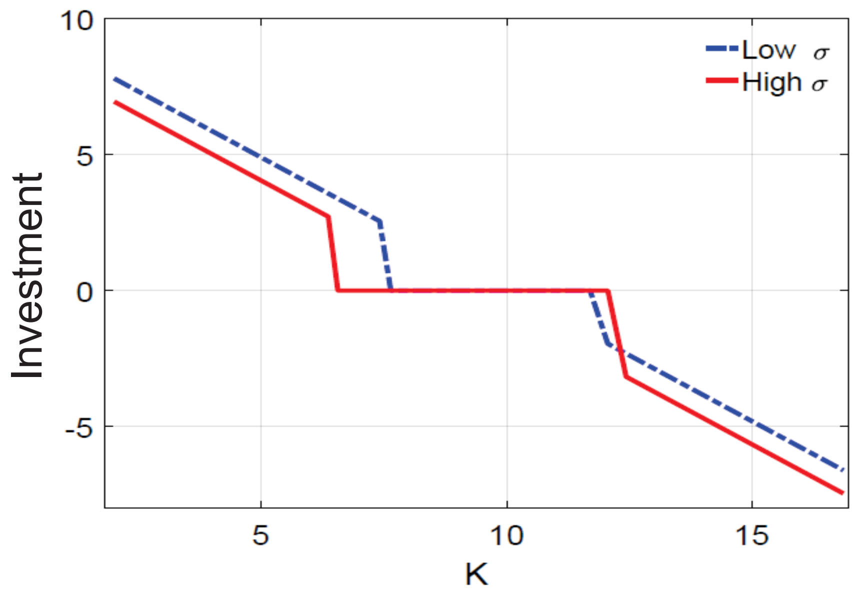


Figure 2B: Benchmark: real and financial fixed costs

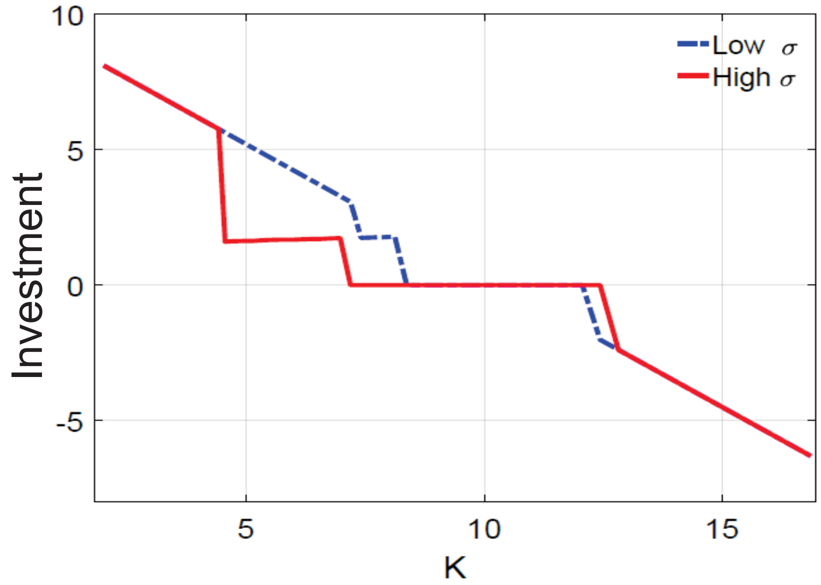
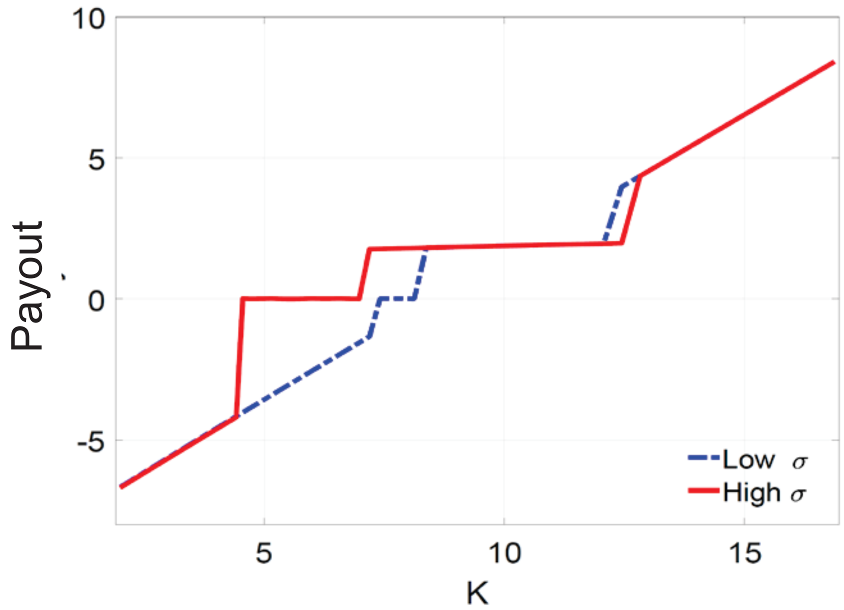
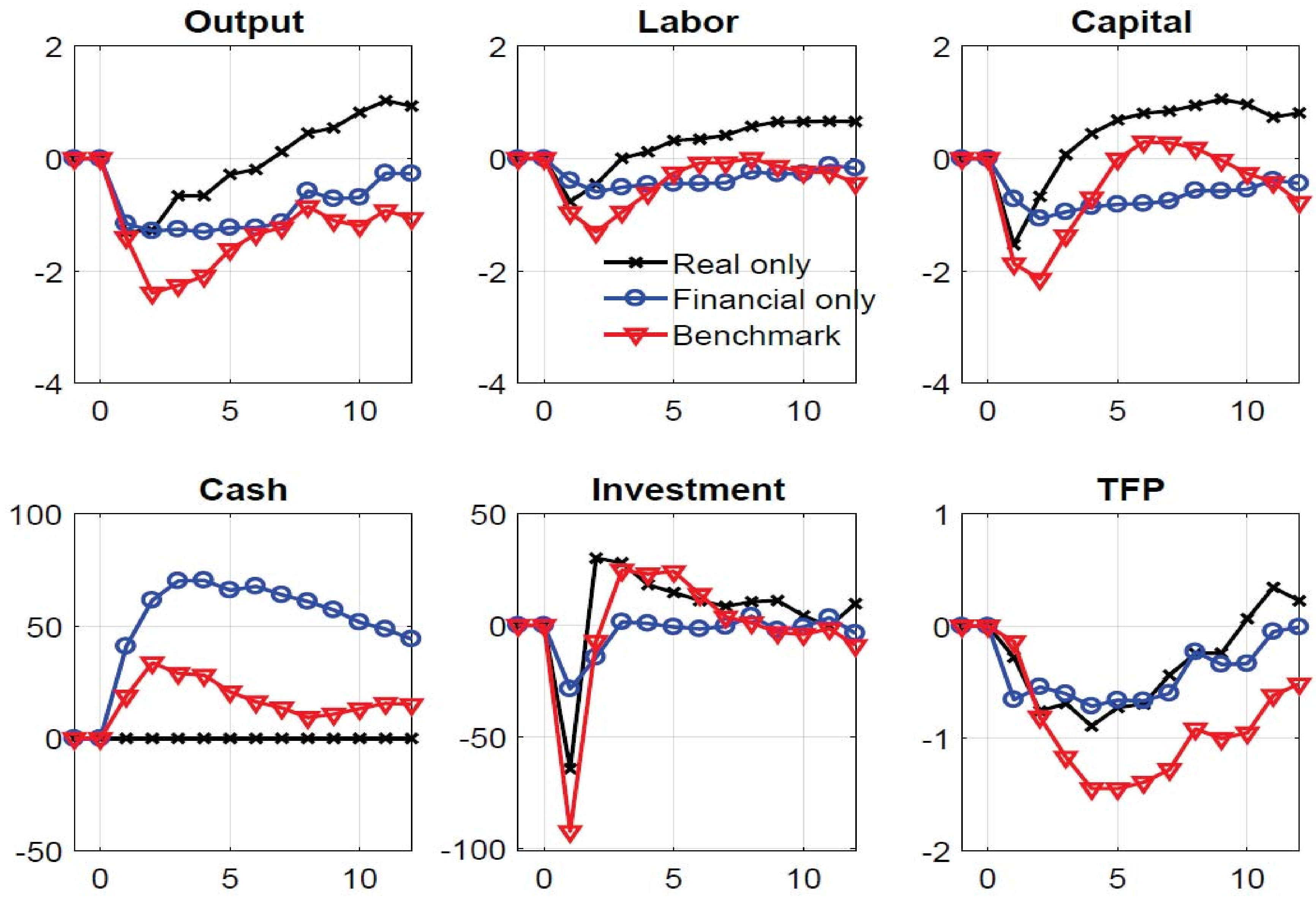


Figure 2C: Payout, real and financial fixed costs



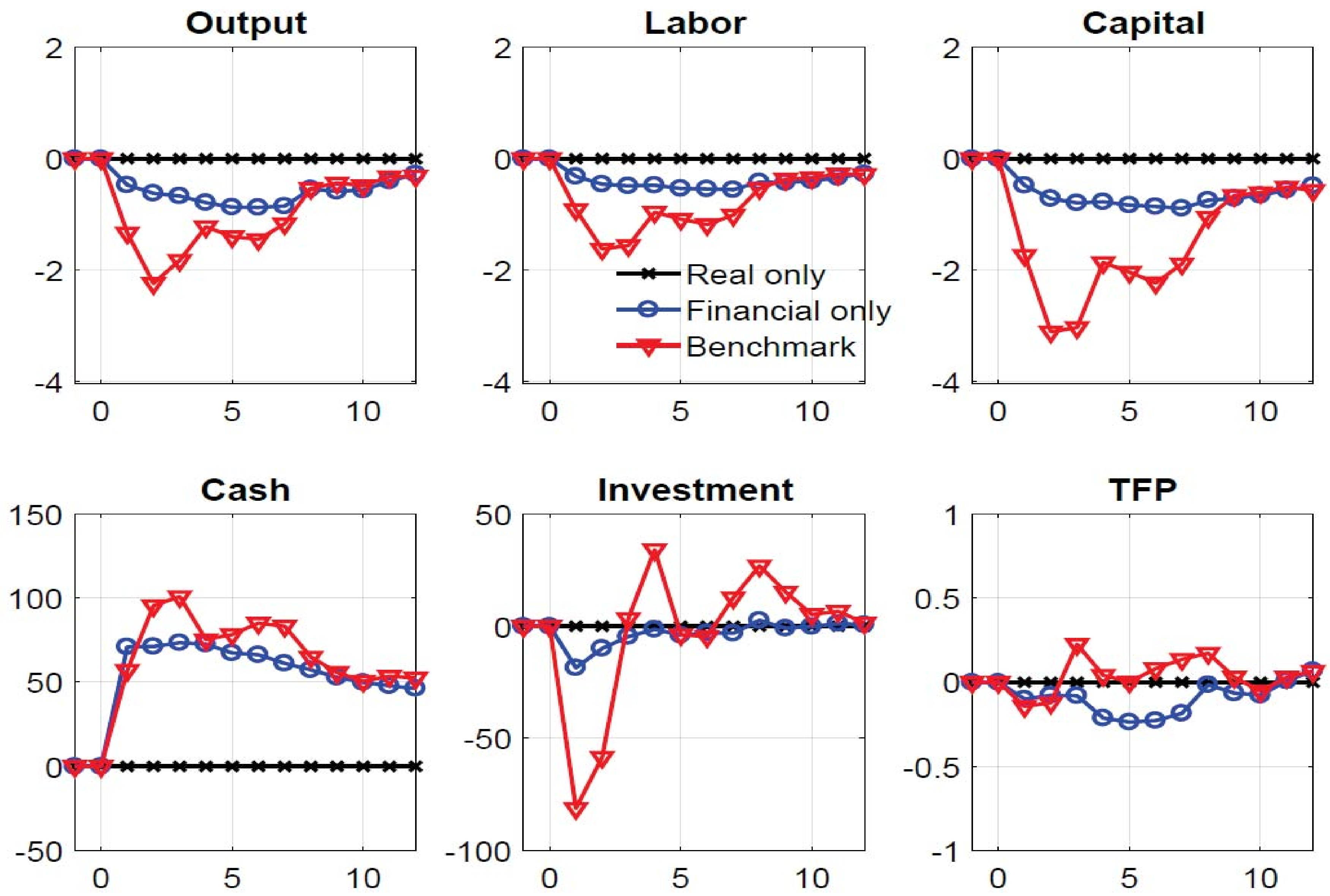
Notes: Figures 2A and 2B plot the optimal investment policies associated with low and high uncertainty shock states of the model with real investment costs only (top left) and the benchmark model (top right), respectively. In both figures, we fix the idiosyncratic productivity and cash at their median 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



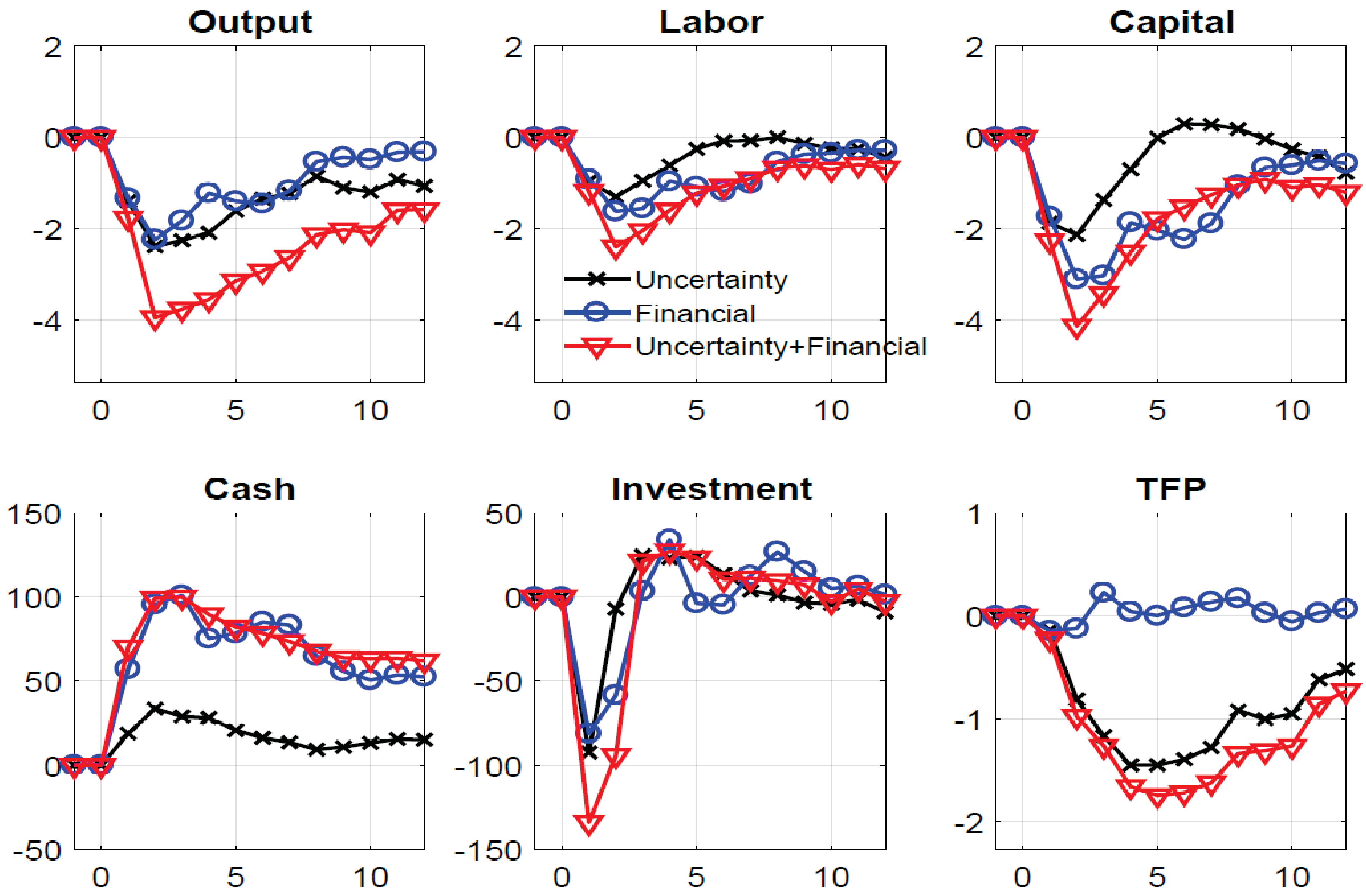
Notes: We plot the percent deviations of average capital, labor, output, cash, investment, and aggregate TFP from their values in quarter 0 of three model specifications: i) the model with real cost only (black x-mark); ii) the model with financial cost only (blue circle), and iii) the benchmark with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



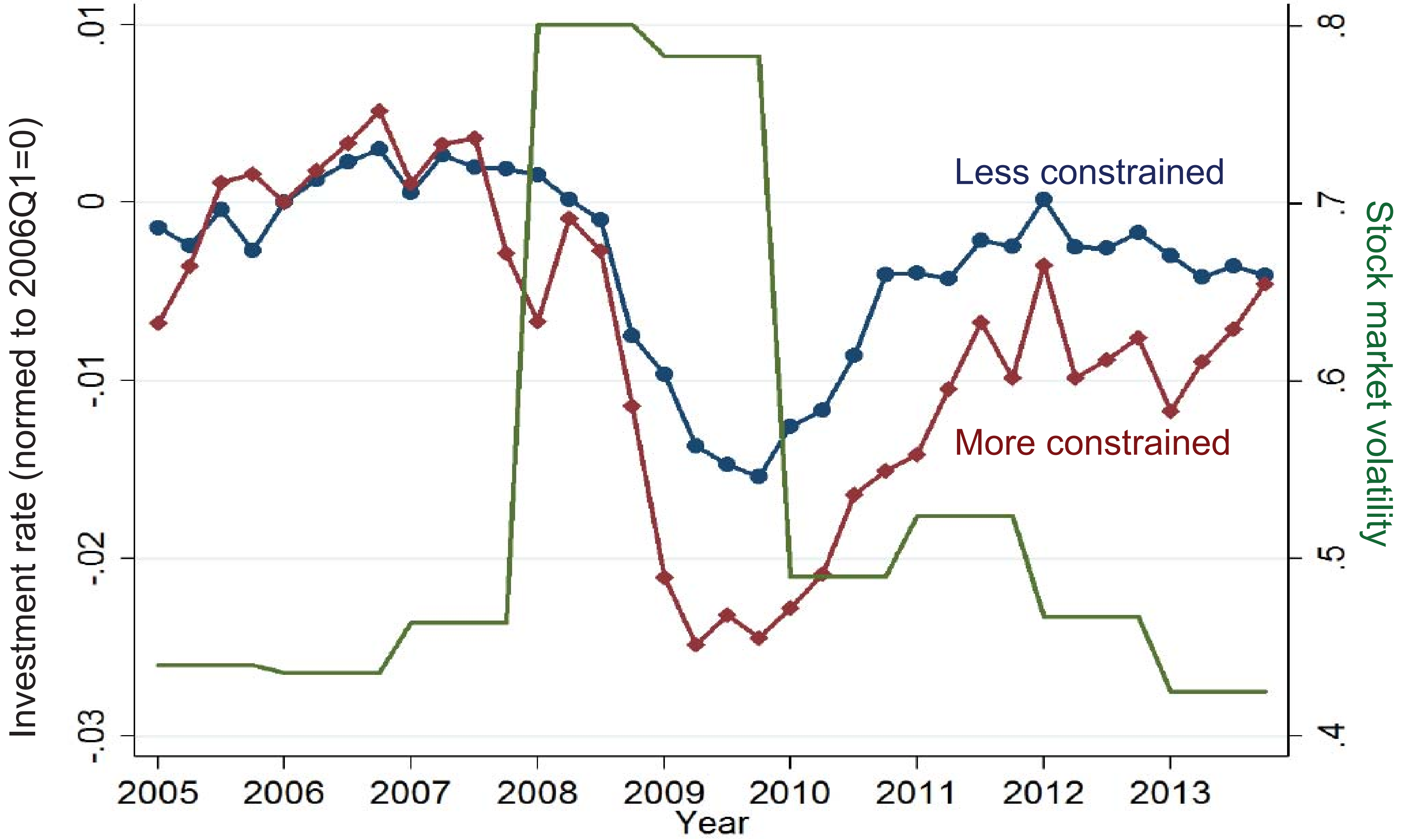
Notes: We plot the percent deviations of average capital, labor, output, cash, investment, and aggregate TFP from their values in quarter 0 of three model specifications: i) the model with real cost only (black x-mark); ii) the model with financial cost only (blue circle), and iii) the benchmark with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



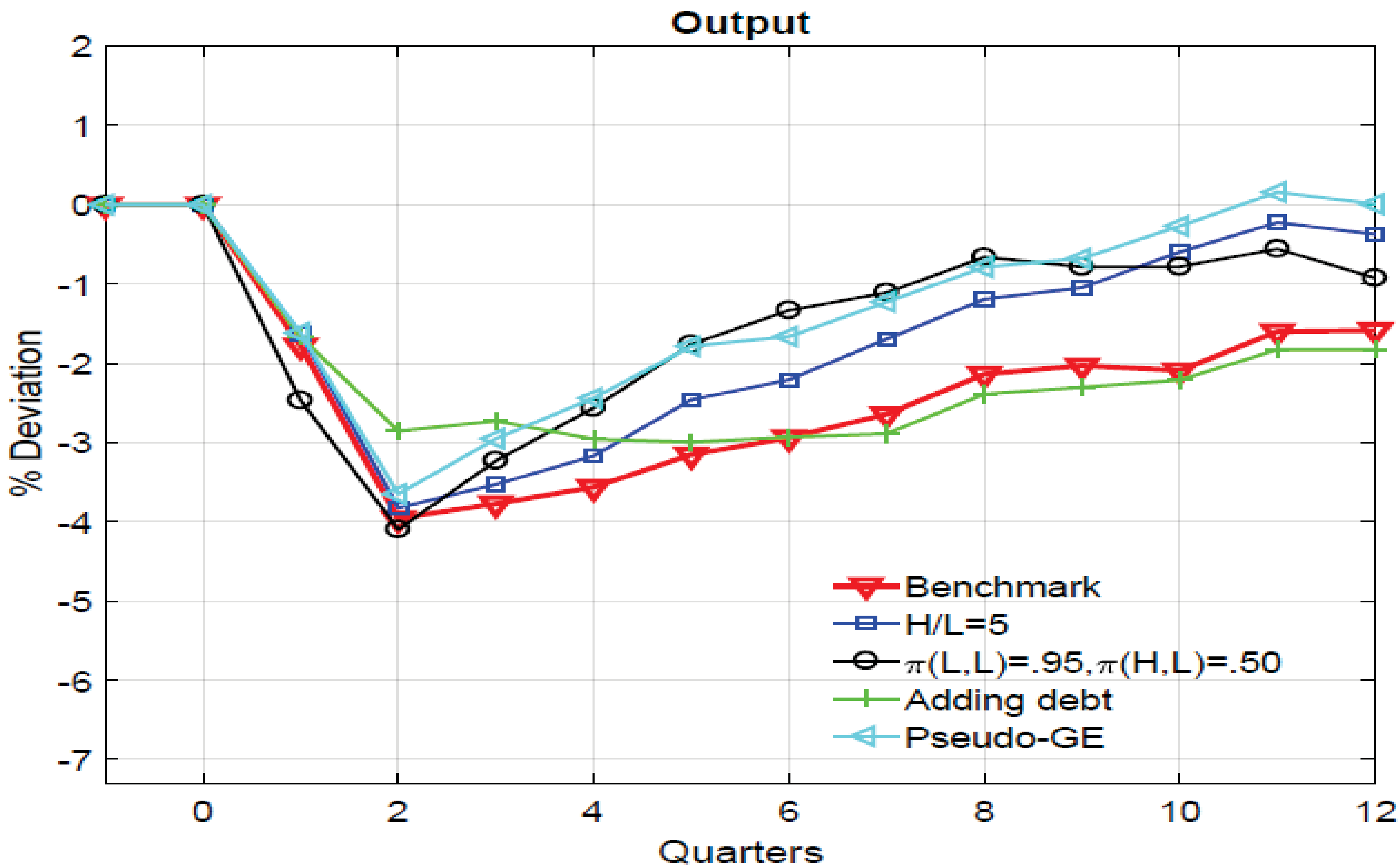
Notes: We plot the percent deviations of average capital, labor, output, cash, investment, and aggregate TFP from their values in quarter 0 of the benchmark model with both real and financial costs. All plots are based on simulations of 30,000 firms of 1000-quarter length. We impose an uncertainty shock (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: 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 daily S&P500 volatility by year, right axis.

Figure 7: Robustness checks 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 model adding debt (green-plus), and the pseudo-GE model (cyan-right 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.